Decision-Oriented Dialogue for Human–AI Collaboration

Jessy Lin^{*1} Nicholas Tomlin^{*1} Jacob Andreas^{2 3} Jason Eisner^{2 4} ¹ UC Berkeley ² Microsoft Semantic Machines ³ MIT ⁴ Johns Hopkins {jessy_lin, nicholas_tomlin}@berkeley.edu {jaandrea, jason.eisner}@microsoft.com

Abstract

We describe a class of tasks called decisionoriented dialogues, in which AI assistants must collaborate with one or more humans via natural language to help them make complex decisions. We formalize three domains in which users face everyday decisions: (1) choosing an assignment of reviewers to conference papers, (2) planning a multi-step itinerary in a city, and (3) negotiating travel plans for a group of friends. In each of these settings, AI assistants and users have disparate abilities that they must combine to arrive at the best decision: assistants can access and process large amounts of information, while users have preferences and constraints external to the system. For each task, we build a dialogue environment where agents receive a reward based on the quality of the final decision they reach. Using these environments, we collect human-human dialogues with humans playing the role of assistant. To compare how current AI assistants communicate in these settings, we present baselines using large language models in self-play. Finally, we highlight a number of challenges models face in decision-oriented dialogues, ranging from efficient communication to reasoning and optimization, and release our environments as a testbed for future modeling work.¹

1 Introduction

Imagine that you are trying to book conference travel with the help of a digital assistant. Your choice of airline is flexible, but you'd rather avoid layovers, want to arrive a day or two before the conference begins, and would like to be able to check in to your hotel as soon as you arrive. Additionally, you're in charge of booking travel for a few of your colleagues, each of whom has their own preferences and budgets, some of whom will be flying in from different cities, but all of whom would like to arrive at roughly the same time and stay in a nearby area. Suddenly, you must manage and communicate about a combinatorial explosion of possible solutions.

Similar optimization problems occur in many everyday situations. Consider consulting a friend about what computer they'd recommend with the best tradeoff of features for your use cases. Or trying to allocate funding from multiple grants to determine which students should work on which projects, while juggling what the individual priorities of each student might be. Or making strategic decisions with your colleagues about which projects your company will take on, in the context of market conditions, and who to hire to manage those projects. All these situations share an underlying decision problem in the face of uncertainty, where communicating and collaborating with others is often critical to arrive at the best solution.

Difficult decision problems like these are precisely where AI assistants could shine. Automated systems can handle large amounts of information and complex computations much better than humans. For example, in cases like travel booking, they can quickly search over a large number of possible itineraries and compute total costs in a way that the average user cannot. They may also be able to efficiently reason under uncertainty about the expected value of decision-relevant information, helping them determine what information may be important to share with or request from the user. On the other hand, these decisions cannot be *fully* automated either. AI assistants complement the user's information and capabilities: people know their preferences and may have other knowledge external to the system, including knowledge about fuzzy real-world constraints that are difficult to formalize in a computer-readable format. To solve these problems, systems need to communicate with users, ideally with a flexible interface such as natural language.

¹Code and data are available at https://github.com/ jlin816/dialop.



Figure 1: Overview of the three collaborative dialogue tasks that we consider. In Optimization, two agents with symmetric access to information play the role of area co-chairs assigning reviewers to conference papers. In Planning, an assistant must collaborate with a user in order to help them plan an itinerary. In Mediation, an assistant must chat with multiple separate users in order to help them resolve a group scheduling problem.

In this paper, we develop a challenging suite of decision problems, benchmark the abilities of current language models on these tasks, and release environments to encourage future work in this area.

We begin by formalizing a class of tasks, decision-oriented dialogues, in which multiple agents must communicate in order to arrive at a joint decision. They are jointly rewarded according to the quality of the decision. Each agent starts out with different information: for example, the user knows their own travel preferences, while the AI assistant has a database of flight and hotel prices. Sharing their information allows them to better assess different travel plans. Critically, however, the large amount of information and (in some tasks) the combinatorial solution space make it unnatural and inefficient for assistants to communicate all of their knowledge to users, or vice versa. Instead, agents must determine what their partners already know and what information is likely to be decisionrelevant, asking clarification questions and making inferences as needed.

Within this class of tasks, we present DialOp, a suite of environments with three everyday domains where humans and agents must collaborate in order to make complicated decisions. (1) In Optimization, two agents take on the role of conference area chairs, assigning reviewers to conference papers when each agent has only has partial information about reviewer-paper similarity. (2) In Planning, an assistant with knowledge of a city must assist a human with building an itinerary based on their preferences. (3) In Mediation, multiple users must collaborate with an assistant in order to resolve group scheduling challenges. For each task, we specify an objective measure of utility based on the quality of the final decision. We first collect human-human dialogues on these tasks in order to establish a reference point for how humans naturally collaborate with each other. We then develop extensible environments for evaluating language models on each task, with support for tool use and chain-of-thought prompting.

We use these environments to benchmark the relative performance of GPT-3 (Brown et al., 2020), both in self-play and in a novel evaluation procedure known as *prompted self-play*, in which AI agents complete partial human dialogues. We then identify several common failure modes of GPT-3 and provide analyses of self-play dialogues. We release all dialogues, environments, and interfaces for human data collection in order to encourage future work that addresses these challenges.

2 Task Formulation

We formalize a *decision-oriented dialogue* (DoD) as a multi-agent problem consisting of a set of agents, an underlying world state W, each agent's partial and possibly noisy observation O_i , a set of legal messages $m \in \mathcal{M}$ (analogous to actions in

an MDP), a reward function over decisions R with parameters θ , and a communication cost function C. The goal of a decision-oriented dialogue is to find a decision that maximizes R while minimizing the communication cost function C. W remains fixed throughout the dialogue. Our problem can be thought of as a decentralized partially observation Markov decision process (Dec-POMDP; Bernstein et al. (2000)) where the actions are "cheap talk" and formal decision messages.

An agent *i*'s policy π_i maps its known information O_i and the dialogue history $\{m_1, \ldots, m_{t-1}\}$ to a new message m_t : $\pi_i(m_t \mid O_i, \{m_1, \dots, m_{t-1}\})$. Agents take turns sending messages by sampling from their policy. Messages may specify a recipient if the number of agents > 2, and are expressed in natural language except for three special formal messages: a proposed decision, a formal acceptance of a decision, and a formal rejection. If an agent sends a proposed decision message and all other agents respond with a formal acceptance, the dialogue ends. When formal proposal decisions are sent, agents may additionally receive noisy observations of the reward of that decision (functions of the reward $f(R_{\theta}(\cdot))$). They can use these observations to make inferences about W and R, and to decide how to respond. Otherwise, the only observations they receive throughout the dialogue are the messages from the other agents.²

To illustrate the information in a DoD, consider the task of planning a travel itinerary that satisfies a user's preferences (Planning, as shown in Figure 1, middle). We represent the underlying world state as a weighted graph W = (V, E, w) whose vertices are potential destinations. A decision is a path W'in W, representing the itinerary. Higher-weighted paths are better and the agents must communicate to improve their knowledge of the edge weights.

In general, we represent the world state W as a weighted graph and the possible decisions as subgraphs W' that satisfy task-specific constraints. Edges and vertices in W have weights $w(e_{ij}), w(v_i)$ that represent rewards (which may be negative) for including them in W'. The optimal decision for this world state is a subgraph $W' \subseteq W$

that maximizes the reward

$$R_{\theta}(W') = \sum_{v \in W'} w(v) + \sum_{e \in W'} w(e) \qquad (1)$$

In principle, the reward function could be be any function of W', but we focus on the linear objective (1). For most practical tasks, the constrained optimization problem could then be expressed as an integer linear programming problem and solved using standard algorithms. We assume edge and vertex weights are determined by their features, represented by feature vectors $\phi(\cdot) \in \mathbb{R}^k$, so that:

$$w(v_i) = \theta^T \phi(v_i)$$

$$w(e_{ij}) = \theta^T \phi(e_{ij})$$
(2)

where θ is a preference vector.

The form of R is common knowledge, but the world state W—in particular the feature vectors and the preferences θ —is only partially observed by each player. Therefore, crucially, players must exchange messages in order to reduce their respective uncertainties about the optimization problem. However, there is a cost to communicating (e.g., time or effort), which agents must trade off with their desire to achieve a good decision. Thus, the overall objective function for a DoD is:

$$\max_{W'\subseteq W,\mathbf{m}} R_{\theta}(W') - \sum_{t} C(m_t)$$
(3)

subject to *task-specific constraints on* W'

In the following sections, we introduce three everyday domains with collaborative decision-making and show how they can be formalized as DoD tasks in our benchmark.

2.1 Optimization

Our first task is an idealized bipartite matching problem, motivated by the scenario of conference organizers assigning reviewers to submitted papers (Figure 1, left). Although reviewer matching is sometimes completely automated via approaches like the Toronto Paper Matching System (TPMS; Charlin and Zemel, 2013), organizers often have incomplete and partially-overlapping knowledge about which reviewers fit which papers. Further, fit cannot necessarily be described on an absolute scale, so when working together on an assignment, organizers must discuss relative edge weights ("Alice would be a better choice than Bob for paper 8"). TPMS could in principle be replaced by an

²In general, the formalism does accommodate settings where an agent can pay to acquire new observations during the dialogue. Simply create other agents that have access to those observations (e.g., sensors), and assign a high cost to communicating with those agents.

AI agent that joins this dialogue as an additional participant.

We consider a simplified version of this problem in which two agents must select a one-to-one correspondence between reviewers and papers. We represent W as a bipartite graph and restrict valid proposals $W' \subseteq W$ to be bipartite matchings. Edge weights represent reviewer-paper affinities, and each agent observes some subset of these weights.

A fuller version of this setting would derive the edge weights from features of the papers and the reviewers (footnote 4 below). This would make communication more interesting, but the underlying optimization problem would remain one of maximum weighted bipartite matching.

2.2 Planning

Next, we consider the scenario in which a user is planning an itinerary in a city with the assistance of a travel agent (Figure 1, middle). While existing systems can assist with parts of travel such as recommendation or booking, they often expect users to provide close-to-full specifications of their requests, rather than working toward a solution together with an assistant (although cf. §8 for a discussion of mixed-initiative dialogue). Ideally, systems would be able to assist us in the comprehensive way a human travel agent would: starting with an under-specified set of "things we'd like to do," comprehensively exploring multi-day itineraries based on the user's preferences and domain knowledge, and iteratively refining the plan with the user based on feedback.

We formalize a small version of this problem as a DoD task where the assistant must plan an itinerary of several sites for a user. The user has preferences about which sites to visit, a budget, and a preference for reducing travel time. Meanwhile, the assistant has access to a database of sites, along with information about their cost, location, and amenities (e.g., outdoor seating). We construct W as a fully-connected graph over the locations, where edge weights represent travel times (and the preference over edge weights is negative). Unlike reviewer matching, this task exhibits asymmetry of information: the assistant has information about vertex features and edge weights, while the user only has information about their own preference vector θ . Due to the budget constraint, the prescribed itinerary length, and the preference to minimize travel, this domain involves aspects of the

knapsack problem, subset-selection problems, and the traveling salesman problem.

2.3 Mediation

Finally, we introduce a coordination scenario where the assistant serves as the role of mediator between multiple users (Figure 1, right). The users are attempting to book flights from their respective cities to all arrive at some shared destination at around the same time, e.g., to meet up for an event or vacation. It is often difficult to negotiate individual constraints and consider all the configurations efficiently. AI assistants may be more suited to guide the group toward a good joint solution, by helping users find options that will work well with the choices of other users as well as their own needs.

We assume that the n users only coordinate through the single assistant.³ In the task, each user wants to choose a flight that is inexpensive and avoids conflicts with the user's calendar commitments, but that arrives close to the arrival times of other players. The assistant has access to each user's flight options and work calendar, but doesn't observe the user's personal calendar, nor the user's preferences about which meetings are important. In the underlying optimization problem, the world state W can be modeled as an complete n-partite graph, where the vertices associated with each user are their flight options. Any two flights for different users are connected by an edge, whose weight indicates how compatible the flights are (i.e., whether they arrive at similar times). Vertex weights are derived from the users' calendars, with important meetings creating a preference against flights (vertices) that conflict with them. The goal is to select a flight for each user so that the induced subgraph W' (with *n* vertices and $\binom{n}{2}$ edges) has high total weight.

3 The DialOp Environments

To instantiate each of these tasks, we release DialOp, an open-source suite of decision-oriented dialogue environments. DialOp environments can be used to evaluate models in self-play as in §6.1, as an underlying API to build human user interfaces for data collection as in §4, or to evaluate models in collaboration with humans.

³Users in such a setting could learn about one another through talking to the assistant. Thus, such systems in practice should also manage privacy issues, which we ignore here.



Figure 2: Data collection and evaluation frameworks. In order to collect human-human dialogues, we built web interfaces which allow humans to play either the user or assistant role for each task. When evaluating language models in self-play, we linearize information from the interface into a text prompt and provide additional tools which allow language models to access information which cannot fit within their context windows.

While other collaborative or task-oriented dialogue tasks are typically evaluated on coarse metrics such as success rate (did the system accomplish the user's goal?) (Li et al., 2016), the reward in a decision-oriented dialogue provides a *graded* measure of communication success: how close to optimal is the final decision? This in turn provides signal on whether models are capable of asking the right questions, sharing the right information, and coordinating efficiently with the user so they can agree on the best course of action—in addition to simply understanding the user's utterances.

In contrast to other dialogue tasks where evaluation is based on supervised datasets, our environments are also *procedurally generated*: the parameters of the underlying decision problem can be randomized to instantiate new dialogue contexts.

Agents interact with the environment with an OpenAI Gym-like interface (Brockman et al., 2016). Agents send messages to the environment and receive messages from other players and any additional observations back. Before each message, agents must output a message type ([message], [propose], [accept], or [reject]), which the environment parses to determine how to interpret the message. Messages are forwarded to other agents. Proposals are parsed and scored; on the next turn the only valid actions for the other agents

are [accept] and [reject]. Formal rejections clear the current proposal, and formal acceptances terminate the dialogue. Below, we describe how the environments implement each of the decision domains we introduce.

Optimization In this task, agents must find the best assignment of k reviewers to k papers. For each game, we sample a random table of reviewerpaper affinity scores (edge weights). Each cell is shown to each player with probability p_{observed} , so that a given cell may be shown to just one player, to both, or to neither. The initial observations o_0 for each player are their observed table values.⁴ In our data collection and experiments we use k = 8, $p_{\text{observed}} = 0.4$. To discourage reviewers from communicating affinity scores in the form of numbers—

⁴There are many ways we could have made the game more realistic. Rather than reveal each score either perfectly or not at all, we could reveal some amount of noisy evidence about the score. Agents can also have asymmetric knowledge. Alternatively, each score could be a function of underlying features—for example, the dot product of the paper's topic vector and the reviewer's topical-expertise vector. We could then selectively reveal evidence about these features—"Alice is an expert on Botany"—rather than about edge weights. If features are correlated, agents may be able to infer features that they do not observe directly. This setup would allow the agents to usefully discuss their knowledge and beliefs about the reviewers and papers (vertex features that affect many edge weights), as well as their resulting assessment of relative affinity scores (edge weights).

which would not be natural in the real-world version of this scenario—we scale all scores shown to each player by a random positive constant, so that they are not comparable across agents but can still be discussed in relative terms such as "X is much better than Y."

Agents take turns sending messages. Either agent is allowed to propose a matching at any point. If the other agent accepts on the next turn, the game ends; otherwise, the proposal is taken off the table and agents continue. The final reward is the sum of edge weights in this matching, normalized by the value of the best matching with the agents' pooled knowledge, computed as an expectation with a uniform prior over values so that rewards are in [0, 1].

Planning In this task, an assistant and a user must book an itinerary of k sites that best satisfies the user's preferences. For each game, we procedurally generate sites (e.g., restaurants, parks, museums) with randomized features such as cuisine type or expected price range. We also procedurally generate a set of s preferences for the user and random preference weights θ representing how much the user cares about each preference. To simulate the fact that people cannot quantify their actual preferences on an absolute scale, the user only observes natural language descriptions of their preferences, without the numerical preference weights. Only the assistant observes the inventory of sites and their features, while only the user observes their preferences. In our data collection and experiments we use k = 3, s = 10.

The assistant and the user take turns sending natural language messages. The assistant can propose a complete or partial itinerary at any point. This proposal's reward (while unknown to the assistant) is automatically computed for the user's convenience, including a breakdown that shows the contributions to the reward from each site, travel times, and budget constraints. With this information, the user can make judgments about aspects of the itinerary (e.g., that it is worth spending extra travel time to visit a particularly desirable site) and determine whether to accept the proposal. The game ends when the user accepts a full itinerary of k sites. The final reward is the score of the itinerary, range-normalized by the scores of the best and worst possible k-site itineraries.

Mediation In this task, two users and one assistant must book the best flight for each user that

satisfies their individual preferences, while being close to each other. On each game, the environment generates a random set of personal calendar events, work calendar events, and importance weights for each event indicating how important it is. The environment also generates a list of flights for each user, each with randomized features for price, arrival time, and departure time. The user observes their own personal and work calendar and flight set, while the assistant observes the work calendars and flight sets of both users (but not their personal calendars). Additionally, the assistant does not observe the importance of each meeting, so it must communicate with the user to determine which events can be missed for the flight. When the assistant proposes a flight to a user, the user observes the score breakdown in terms of missed meetings, price, and closeness to the other user's flight (when known). The game ends when all users accept the assistant's proposals. The final reward is the sum of their scores, range-normalized by the scores of the best and worst pairs of flights.

4 The DialOp Dataset

In order to study the communication strategies used by humans and establish baseline performance numbers for each task, we collected a set of humanhuman dialogues. For each task, we built a multiplayer online interface and collected high-quality human-human dialogues using a mixture of Amazon Mechanical Turk and in-house Microsoft data annotators, resulting in a total of 409 dialogues, consisting of 5253 messages and over 58K words across domains. Human players take a median time of 8min 19sec across tasks. Humans achieve an average of roughly 90% of the maximum possible score on both the optimization and planning domains, and close to 100% performance in the mediation domain. We report additional dataset statistics in Table 2 in the appendix.

In each task, each annotator played the role of an assistant or user. For ease of play, annotators were not required to take turns, but used a chat interface where they could send a message at any time. Consecutive messages from the same annotator were concatenated into a "turn."

Although real-world users know their own preferences, our annotators are emulating users that we have generated programmatically, so we must tell them what their preferences are. This setup gives us full knowledge of user preferences so that



Figure 3: An annotated example of a human-human dialogue and a model-model self-play dialogue with GPT-3 in Planning. While humans generally exhibit diverse and flexible strategies and reach good solutions, self-play dialogues tend to be repetitive, and the assistant makes mediocre proposals and often hallucinates. We discuss more analysis in §7.

we can objectively evaluate the quality of the decision. We simulate the fact that internal preferences may be comparative or fuzzy by scaling numerical values (in Optimization) or not showing numerical values until a proposal is presented. This design encourages realistic behavior in the dialogues: it is easier to make comparisons between travel itineraries and point to specific aspects you like and dislike, rather than fully specify an itinerary you would like.

As depicted in Figure 2 for Planning, humans had access to the same information as models receive in the task, but presented in a graphical user interface (UI) rather than purely in text:

Optimization Both annotators see a spreadsheet with their scaled known table values. They can click on cells in the spreadsheet to make a proposal.

Planning The human assistant sees a map of all the locations, allowing them to visually estimate distances. They can fill in events into a proposed

itinerary, which auto-calculates the exact distances. They can click on a site to see its features or filter sites on the map with checkboxes and sliders. The user initially only sees a plain-text list of their travel preferences (e.g., "like seafood, Japanese") without the preference weight values. When the assistant sends a proposed (partial or full) itinerary, the user sees the features of the proposed sites and a scorecard breaking down the total score by event, travel distance, and budget.

Mediation Users see a three-day calendar with events and a list of flights with times and prices. Events are labeled with a numerical value for their importance. The human assistants see the calendars and flight lists for both users. When the assistant makes a proposal to one or both users, they see the proposed flight overlaid on their calendar and a scorecard breaking down the total score with the penalty for missing calendar events, arriving at a different time from the other user, and flight price. For more details on the data collection set up and

interface screenshots, refer to the appendix. We also release the code to run the UIs for the tasks.

5 Baseline Models

We believe that AI agents for decision-oriented dialogue will benefit from incorporating explicit reasoning over possible world states and possible decisions. However, as a baseline approach, this paper evaluates few-shot prompted LLMs as the AI agents. These have the benefit that they can attempt a wide variety of dialogue interactions without the need for domain-specific training or modeling. In particular, we focus our evaluations on the instruction-tuned GPT-3 model known as text-davinci-003 (Brown et al., 2020; Ouyang et al., 2022). For Optimization, we prompt with two human-human dialogue examples from the dataset; for the others we prompt with one, due to context length limitations. If models fail to generate a valid message (e.g., user simulator model attempting to send proposals), we append the generated message to the prompt, along with any error message from the game, and continue generating, allowing the model to revise its previous generation. Below, we describe how models are prompted with the information for each task. Refer to Appendix E for the full prompts.

Optimization Both players see a partial table of weights matching reviewers and papers for this task. We prompt the model with the linearized table, formatted as a CSV.

Planning For the user simulator model, we prompt with the natural language list of travel preferences as the context. The agent has access to a database of sites with features. We take a modular tool use approach, where the agent model accesses information in the database by writing search queries rather than conditioning directly on the database itself. The search queries are executed by a query executor model that conditions on the database and generates the result for the new query. We hand-write several example queries in a simple domain-specific language where the agent can return specific fields (e.g. name, category, price) of a site, filter over fields, sort_by field values (including distance_to another destination), and search by text_query in freeform natural language. While the DSL examples guide the set of searches the agent can perform, the query executor can generalize to new searches beyond the

demonstrations. We augment the 1-shot example in agent's prompt with examples of queries in the DSL along with their results throughout the dialogue and provide the query executor with query and result examples. Delegating searches over the database to the query executor reduces context length restrictions and allows the agent model to filter for relevant information from the database with an abstracted query layer. Future approaches may consider using larger context length models and directly conditioning on the database.

This task requires particularly complex reasoning to search based on the dialogue (on the agent side) and decide whether to accept an itinerary based on the scores (on the user side). We also augment the dialogues in the user and agent prompt with [think] steps such as "I am losing the most points from the travel time between events. I should reject the proposal..." based on ReAct (Yao et al., 2022) to provide the model with reasoning examples.

Mediation Each user can see their set of flights, private calendar, and shared work calendar while the agent can see flights and shared calendars (without event importance values) for both players. We prompt models with the list of all flights and calendar events. The environment allows the agent to talk to either player; generally, deciding which user to talk to is itself a strategic decision. We adopt a simple turn-taking strategy where we iterate roundrobin through all players; on the agent's turn, they are prompted with You to and choose which user to send the message to by generating either 0 or 1 (e.g. "You to 0").

6 Evaluation

In this section, we compare the performance of humans and AI agents on our tasks. While we are ultimately interested in how well AI agents can perform in collaboration with human partners, we introduce two automatic evaluation setups which serve as proxies for human evaluation. Our experiments aim to understand: (1) how well do current models perform in decision-oriented dialogues (as evaluated in self-play; §6.1) and (2) how well can models comprehend human dialogues, as a proxy for eventual collaboration with real people (as evaluated in prompted self-play; §6.2)?



Figure 4: Self-play scores and dialogue lengths in words, compared to human-human dialogues. Models achieve lower scores on average, and also tend to have longer dialogues. Marginal distributions for the # words and score are shown as histograms, and the average score of a randomly selected proposal is shown for each task as a dashed gray line. Mean and SEM numbers can be found in Table 1.

6.1 Self-Play

First, we evaluate how well models can collaborate with each other in self-play. We prompt each model with the private knowledge for a player. On each step of the environment, we generate from the model whose turn it is (assistant or user simulator(s)) and append the outputted message to both models' context. We repeatedly generate from the model until a proposal is made and accepted.

In Figure 4, we show human-human and modelmodel scores against the number of words in the dialogue. For a fair comparison, we prompt models with the same randomly generated instances as the human-human dialogues in the evaluation dataset, although future agents can also generally be evaluated on new random instances generated from the environment. In gray, we show the performance of a naive rule-based baseline that selects a random proposal from the set of all possible proposals. Compared to humans, models tend to have longer dialogues than humans and achieve less optimal solutions. Models significantly outperform the baseline on both the itinerary planning and mediation tasks but do slightly worse than random chance on the reviewer matching task, signaling that they struggle with its underlying optimization problem. These results suggest that models have yet to close the gap to human performance in communicating efficiently to collaborate on good solutions.

6.2 Prompted Self-Play

Even agents that perform well in self-play may not perform well in collaboration with humans (Carroll et al., 2019). This disparity exists because humans often use different and more diverse strategies than artificial agents, particularly if agent strategies arise from explicit optimization of an objective.

To bridge this gap, we propose a new mode of automatic evaluation known as prompted self-play (PSP), in which dialogues are initialized with the prefix of a human-human dialogue and then continued by the model. Given a human-human dialogue from our dataset, we test how models perform if they are provided with 50% of the dialogue, 75% of the dialogue, and everything except the final proposal, and then complete the rest of the dialogue via self-play. PSP tests additional capabilities beyond self-play: in PSP, the dialogue history contains information that the human-human pair has talked about already, making it easier to find good solutions if models are able to understand and reason over the information to make a proposal. Additionally, models should do some degree of belief modeling about what the human being simulated knows to communicate efficiently; for example, models ought to avoid asking about information already implied by previous utterances. Finally, prompting in this way encourages models to complete dialogues "in the style" of the human-human pair in the prefix. As a result, PSP both tests whether models can flexibly continue dialogues demonstrating different strategies (e.g. with one agent taking most of the initiative), and whether assistants can collaborate with a diverse range of humans, similar to population play and fictitious self-play evaluation (Jaderberg et al., 2019; Strouse et al., 2021).



Figure 5: Prompted self-play results for all three tasks, compared to human results. For each setting, we initialize dialogues with 50% and 75% of a corresponding human game and let GPT-3 complete the dialogue. In the *proposal* setting, we prompt the model with an entire human dialogue except for the final proposal and force the model to end the game immediately. The average score of a randomly selected proposal is shown for each task as a dashed gray line. (*) For reference, we show the mean score of models in self-play, although we note that they are not prompted to end the dialogue at some length like the other PSP conditions.

We bias models to output dialogues that are approximately the same length as the corresponding human-human dialogue (cf. Appendix E). Figure 5 shows average PSP performance for each task. In Planning, models perform better with additional human data in the prompt, suggesting that they are at least partially capable of integrating information from the human-human prefix. However, there is a substantial gap between the proposal condition and human-human dialogue scores, indicating that models struggle to perform the final optimization step of choosing the best solution given the entire dialogue history. Meanwhile, in Optimization, models fail across all PSP conditions; this occurs because the final step of the reviewer matching game involves integrating the discussed values to compute a bipartite matching, which is difficult for models. Finally, in Mediation, models score well above a random baseline in all PSP conditions but do not perform better with additional humanhuman dialogue context, suggesting that they can meaningfully communicate about the task but don't make the optimal final proposal. In the future, tool use could potentially greatly improve performance on this task, particularly with tools that can specifically handle the optimization part of the problem.

7 Analysis

In order to quantify the strategies used in humanhuman dialogues, we used GPT-3 to annotate dialogues at the level of individual messages. Based on manual inspection of a small set of games, we devised a list of message types: (1) *share*, in which agents provide information about their preferences; (2) *query*, in which agents ask each other for information; (3) *affirm*, in which agents agree with each other and/or ground incoming messages; (4) *explain*, in which agents provide justification for a previous message or action; (5) *meta*, in which agents engage in discussion about high-level strategies or meta-game details; (6) *revise*, in which agents correct earlier statements; or (7) *miscellany*, which includes other messages such as greetings. Each message may have multiple message types. We prompted GPT-3 to generate message annotations for each of the 5253 messages using two hand-annotated example dialogues. We provide additional details and data statistics in the appendix.

Most dialogues are focused on exchanging information: of the message types, we find that human agents most commonly share or query for information. In the Optimization game, agents send twice as many share messages as any other type of message, often sending information about individual cells in their observed tables. One strategy used by humans involves both players sharing all observed information and then making a decision at the end of the game. This strategy is most tractable in Optimization game, where players have a relatively small observation space. However, this strategy leads to exceptionally long dialogues, even in Optimization, and is not the most common approach. Meanwhile, in the Planning and Mediation games, which have asymmetric information and roles, agents are more likely to query for information or engage in meta-game discussion in order to learn what information the other agent can see. Agents must still share information, but assistants for both of these tasks have access to an exceptionally large amount of information which cannot be fully shared with the users.

We also provide a breakdown of message types



Figure 6: Kernel density estimates of message types in human-human dialogues plotted against their position within a dialogue. Message types were automatically annotated using few-shot prompting with GPT-3.

over the time-course of dialogues in Figure 6. As expected, many interactions begin with greetings, which is evidenced by a spike in the *miscellany* category at the beginning of all three plots. In the Planning and Mediation tasks, agents are more likely to *query* at the beginnings of games and then respond with *share* messages shortly afterward. Finally, *affirm* messages, although rare, are most likely to appear at the end of dialogues, once common ground has been established.

Qualitatively, we show a human-human dialogue side-by-side with a self-play dialogue in Figure 3. We generally observe across the human dialogues that human-human pairs exhibit diverse strategies in (1) **user-agent initiative**: in some dialogues, users are proactive in sharing relevant information, while in others agents make directed queries to narrow down the set of proposals; and (2) **coordination strategies**: working incrementally from partial proposals, backtracking, and more.

In self-play dialogues, current LLMs are capable of carrying on natural dialogues that partly address the user's preferences and find good solutions. However, they generally tend to be formulaic and repetitive, and hallucinations are a problem, as with other tasks involving language models. Critically, models ask general questions such as "Do you have any other preferences?" and sometimes slightly more specific ones such as "Do you have a price point?", but the questions are not goal-directed in eliciting decision-critical information. In contrast, human assistants ask questions that help them decide between proposals or narrow down the search space. Finally, models fail to do the optimization step of the proposal (as supported by our PSP results): proposals are often only slightly better than random, and do not improve drastically over the course of the dialogue. This suggests that our task targets many of the critical capabilities missing

from current models, such as reasoning, asking clarification questions, grounding to external sources, and hallucination.

8 Related Work

Task-Oriented Dialogue Our work may be viewed as an extension of task-oriented dialogue, where a system must assist a user with accomplishing a goal, such as hotel booking or calendar scheduling (Budzianowski et al., 2018; Wei et al., 2018; Semantic Machines et al., 2020). Most taskoriented dialogue settings involve helping a user who is seeking out a specific piece of information ("what is a vegetarian Italian restaurant nearby?") or wants to take an action ("change my flight to tuesday"). Systems are typically evaluated with coarse metrics such as success rate (e.g. at returning the right hotel information requested by a user) or word overlap with human-human dialogues. In contrast, our tasks are grounded in underlying optimization problems, where the quality of the final solution provides a richer measure of communicative success. All agents must engage in information-seeking and understand intents in the course of a dialogue decision problem, but furthermore have to take initiative to share and query information to collaborate on a good solution. In this sense, our work is more similar to early work on task-oriented dialogue in mixed-initiative settings (Novick and Sutton, 1997; Horvitz, 1999) such as TRAINS (Allen et al., 1995) and TRIPS (Allen and Ferguson, 2002), in which users had to collaborate with a computer agent in order to solve planning problems such as train routing. Our task includes many similar design elements but is aimed at building general dialogue systems without the significant domain-specific engineering that went into projects like TRAINS and TRIPS.

Grounded Dialogue Another class of dialogue tasks are grounded dialogue settings such as Cards (Potts, 2012; Vogel et al., 2013), CerealBar (Suhr et al., 2019), MutualFriends (He et al., 2017), and OneCommon (Udagawa and Aizawa, 2019), where agents communicate in a game-like setting to achieve a goal. These tasks are often situated in a multimodal environment with visual elements or external knowledge. Our task also has many of these elements, but we focus on domains with everyday optimization problems where successful communication could be useful to people. Our work also shares elements in common with negotiation dialogue tasks such as Deal or No Deal (Lewis et al., 2017) and Craigslist Bargaining (He et al., 2018), but we focus on cooperative scenarios in which all agents share the same objective.

Large Language Models Our goal of building task-general dialogue agents motivates the use of large language models (LLMs) such as GPT-3 (Brown et al., 2020; Ouyang et al., 2022), PaLM (Chowdhery et al., 2022), or LLaMA (Touvron et al., 2023). Recent work has focused on using language models as dialogue agents, including OpenAI's ChatGPT, Microsoft's Sydney, Anthropic's Claude, and Google's LAMDA (Thoppilan et al., 2022) and Bard. Current-era language models are known to struggle with aspects of our tasks, such as mathematical reasoning (Hendrycks et al., 2021), explicit state tracking (Li et al., 2021), pragmatics (Fried et al., 2022), and theory of mind (Sap et al., 2022). However, recent work in scratchpad prompting (Nye et al., 2021), chain-of-thought reasoning (Wei et al., 2022), and external tool use (Schick et al., 2023) has sought to address these problems. We build baseline models with similar approaches in our setting. While LLMs can perform reasonably well in some of our settings, we show that they cannot consistently handle dialogues with complex decision problems as well as humans.

Human–AI Collaboration Our task may also be viewed as a cooperative multi-agent setting (Dafoe et al., 2020). Research in human-AI collaboration and multi-agent reinforcement learning has also formalized tasks that require collaborating strategically with other agents on a shared goal, through tasks such as Overcooked (Carroll et al., 2019), Hanabi (Bard et al., 2020), and Diplomacy (Bakhtin et al., 2022). Our evaluation methodology is adapted from these tasks, where

methods like population play and fictitious selfplay are often used as proxies for human evaluation in addition to self-play (Heinrich et al., 2015; Strouse et al., 2021). In human–AI collaboration, cooperative tasks have been formulated in game-theoretic terms where agents use signals from the user such as demonstrations, feedback, or language (Jeon et al., 2020; Lin et al., 2022) to explicitly optimize for assistive behavior (Hadfield-Menell et al., 2016; Sadigh et al., 2016). In our work, we are similarly interested in formalizing settings where agents should explicitly optimize for human assistance in the course of dialogue.

9 Conclusion

In this paper, we presented data, environments, and model baselines for a class of tasks we call *decision-oriented dialogues*. Across all task settings, current-era language models did not perform as well as humans, suggesting failures in their ability to communicate efficiently and reason in structured real-world optimization problems. Future modeling work in this domain may seek to integrate tools and inference techniques which would allow language models to compute optimal decisions for these types of problems while maintaining their flexible communication and collaboration skills.

References

- James F. Allen and George Ferguson. 2002. Humanmachine collaborative planning.
- James F Allen, Lenhart K Schubert, George Ferguson, Peter Heeman, Chung Hee Hwang, Tsuneaki Kato, Marc Light, Nathaniel Martin, Bradford Miller, Massimo Poesio, et al. 1995. The trains project: A case study in building a conversational planning agent. *Journal of Experimental & Theoretical Artificial Intelligence*, 7(1):7–48.
- Anton Bakhtin, Noam Brown, Emily Dinan, Gabriele Farina, Colin Flaherty, Daniel Fried, Andrew Goff, Jonathan Gray, Hengyuan Hu, Athul Paul Jacob, Mojtaba Komeili, Karthik Konath, Minae Kwon, Adam Lerer, Mike Lewis, Alexander H. Miller, Sasha Mitts, Adithya Renduchintala, Stephen Roller, Dirk Rowe, Weiyan Shi, Joe Spisak, Alexander Wei, David Wu, Hugh Zhang, and Markus Zijlstra. 2022. Humanlevel play in the game of <i>diplomacy</i> by combining language models with strategic reasoning. *Science*, 378(6624):1067–1074.
- Nolan Bard, Jakob N. Foerster, Sarath Chandar, Neil Burch, Marc Lanctot, H. Francis Song, Emilio Parisotto, Vincent Dumoulin, Subhodeep Moitra, Edward Hughes, Iain Dunning, Shibl Mourad, Hugo

Larochelle, Marc G. Bellemare, and Michael Bowling. 2020. The hanabi challenge: A new frontier for ai research. *Artificial Intelligence*, 280:103216.

- Daniel S. Bernstein, Shlomo Zilberstein, and Neil Immerman. 2000. The complexity of decentralized control of markov decision processes. In *Proceedings* of the Sixteenth Conference on Uncertainty in Artificial Intelligence, UAI'00, page 32–37, San Francisco, CA, USA. Morgan Kaufmann Publishers Inc.
- Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. 2016. Openai gym.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In Advances in Neural Information Processing Systems, volume 33, pages 1877–1901. Curran Associates, Inc.
- Paweł Budzianowski, Tsung-Hsien Wen, Bo-Hsiang Tseng, Iñigo Casanueva, Stefan Ultes, Osman Ramadan, and Milica Gašić. 2018. MultiWOZ - a largescale multi-domain Wizard-of-Oz dataset for taskoriented dialogue modelling. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 5016–5026, Brussels, Belgium. Association for Computational Linguistics.
- Micah Carroll, Rohin Shah, Mark K Ho, Tom Griffiths, Sanjit Seshia, Pieter Abbeel, and Anca Dragan. 2019. On the utility of learning about humans for human-ai coordination. In *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc.
- Laurent Charlin and Richard S. Zemel. 2013. The toronto paper matching system: An automated paper-reviewer assignment system.
- Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. 2022. Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*.
- Allan Dafoe, Edward Hughes, Yoram Bachrach, Tantum Collins, Kevin R. McKee, Joel Z. Leibo, K. Larson, and Thore Graepel. 2020. Open problems in cooperative ai. *ArXiv*, abs/2012.08630.
- Daniel Fried, Nicholas Tomlin, Jennifer Hu, Roma Patel, and Aida Nematzadeh. 2022. Pragmatics in grounded language learning: Phenomena, tasks, and modeling approaches. *arXiv preprint arXiv:2211.08371*.

- Dylan Hadfield-Menell, Stuart J Russell, Pieter Abbeel, and Anca Dragan. 2016. Cooperative inverse reinforcement learning. In *Advances in Neural Information Processing Systems*, volume 29. Curran Associates, Inc.
- He He, Anusha Balakrishnan, Mihail Eric, and Percy Liang. 2017. Learning symmetric collaborative dialogue agents with dynamic knowledge graph embeddings. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1766–1776, Vancouver, Canada. Association for Computational Linguistics.
- He He, Derek Chen, Anusha Balakrishnan, and Percy Liang. 2018. Decoupling strategy and generation in negotiation dialogues. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2333–2343, Brussels, Belgium. Association for Computational Linguistics.
- Johannes Heinrich, Marc Lanctot, and David Silver. 2015. Fictitious self-play in extensive-form games. In *Proceedings of the 32nd International Conference* on Machine Learning, volume 37 of *Proceedings of* Machine Learning Research, pages 805–813, Lille, France. PMLR.
- Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. 2021. Measuring mathematical problem solving with the math dataset. *arXiv preprint arXiv:2103.03874*.
- Eric Horvitz. 1999. Principles of mixed-initiative user interfaces. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*, pages 159– 166.
- Max Jaderberg, Wojciech M. Czarnecki, Iain Dunning, Luke Marris, Guy Lever, Antonio Garcia Castañeda, Charles Beattie, Neil C. Rabinowitz, Ari S. Morcos, Avraham Ruderman, Nicolas Sonnerat, Tim Green, Louise Deason, Joel Z. Leibo, David Silver, Demis Hassabis, Koray Kavukcuoglu, and Thore Graepel. 2019. Human-level performance in 3d multiplayer games with population-based reinforcement learning. *Science*, 364(6443):859–865.
- Hong Jun Jeon, Smitha Milli, and Anca Dragan. 2020. Reward-rational (implicit) choice: A unifying formalism for reward learning. In Advances in Neural Information Processing Systems, volume 33, pages 4415–4426. Curran Associates, Inc.
- Mike Lewis, Denis Yarats, Yann Dauphin, Devi Parikh, and Dhruv Batra. 2017. Deal or no deal? end-toend learning of negotiation dialogues. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 2443–2453, Copenhagen, Denmark. Association for Computational Linguistics.
- Belinda Z. Li, Maxwell Nye, and Jacob Andreas. 2021. Implicit representations of meaning in neural language models. In *Proceedings of the 59th Annual*

Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 1813–1827, Online. Association for Computational Linguistics.

- Jiwei Li, Will Monroe, Alan Ritter, Dan Jurafsky, Michel Galley, and Jianfeng Gao. 2016. Deep reinforcement learning for dialogue generation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1192– 1202, Austin, Texas. Association for Computational Linguistics.
- Jessy Lin, Daniel Fried, Dan Klein, and Anca Dragan. 2022. Inferring rewards from language in context. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 8546–8560, Dublin, Ireland. Association for Computational Linguistics.
- David G Novick and Stephen Sutton. 1997. What is mixed-initiative interaction. In *Proceedings of the AAAI spring symposium on computational models for mixed initiative interaction*, volume 2, page 12.
- Maxwell Nye, Anders Johan Andreassen, Guy Gur-Ari, Henryk Michalewski, Jacob Austin, David Bieber, David Dohan, Aitor Lewkowycz, Maarten Bosma, David Luan, et al. 2021. Show your work: Scratchpads for intermediate computation with language models. *arXiv preprint arXiv:2112.00114*.
- Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. arXiv preprint arXiv:2203.02155.
- Christopher Potts. 2012. Goal-driven answers in the cards dialogue corpus. In *Proceedings of the 30th West Coast Conference on Formal Linguistics*, pages 1–20. Cascadilla Proceedings Project.
- Dorsa Sadigh, Shankar Sastry, Sanjit A. Seshia, and Anca D. Dragan. 2016. Planning for autonomous cars that leverage effects on human actions. In *Proceedings of Robotics: Science and Systems*, AnnArbor, Michigan.
- Maarten Sap, Ronan LeBras, Daniel Fried, and Yejin Choi. 2022. Neural theory-of-mind? on the limits of social intelligence in large lms. *arXiv preprint arXiv:2210.13312*.
- Timo Schick, Jane Dwivedi-Yu, Roberto Dessì, Roberta Raileanu, Maria Lomeli, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. 2023. Toolformer: Language models can teach themselves to use tools. *arXiv preprint arXiv:2302.04761*.
- Semantic Machines, Jacob Andreas, John Bufe, David Burkett, Charles Chen, Josh Clausman, Jean Crawford, Kate Crim, Jordan DeLoach, Leah Dorner, Jason Eisner, Hao Fang, Alan Guo, David Hall, Kristin

Hayes, Kellie Hill, Diana Ho, Wendy Iwaszuk, Smriti Jha, Dan Klein, Jayant Krishnamurthy, Theo Lanman, Percy Liang, Christopher H. Lin, Ilya Lintsbakh, Andy McGovern, Aleksandr Nisnevich, Adam Pauls, Dmitrij Petters, Brent Read, Dan Roth, Subhro Roy, Jesse Rusak, Beth Short, Div Slomin, Ben Snyder, Stephon Striplin, Yu Su, Zachary Tellman, Sam Thomson, Andrei Vorobev, Izabela Witoszko, Jason Wolfe, Abby Wray, Yuchen Zhang, and Alexander Zotov. 2020. Task-Oriented Dialogue as Dataflow Synthesis. *Transactions of the Association for Computational Linguistics*, 8:556–571.

- DJ Strouse, Kevin McKee, Matt Botvinick, Edward Hughes, and Richard Everett. 2021. Collaborating with humans without human data. In *Advances in Neural Information Processing Systems*, volume 34, pages 14502–14515. Curran Associates, Inc.
- Alane Suhr, Claudia Yan, Jack Schluger, Stanley Yu, Hadi Khader, Marwa Mouallem, Iris Zhang, and Yoav Artzi. 2019. Executing instructions in situated collaborative interactions. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 2119–2130, Hong Kong, China. Association for Computational Linguistics.
- Romal Thoppilan, Daniel De Freitas, Jamie Hall, Noam Shazeer, Apoorv Kulshreshtha, Heng-Tze Cheng, Alicia Jin, Taylor Bos, Leslie Baker, Yu Du, et al. 2022. Lamda: Language models for dialog applications. arXiv preprint arXiv:2201.08239.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. 2023. Llama: Open and efficient foundation language models. arXiv preprint arXiv:2302.13971.
- Takuma Udagawa and Akiko Aizawa. 2019. A natural language corpus of common grounding under continuous and partially-observable context. *Proceedings of the AAAI Conference on Artificial Intelligence*, 33(01):7120–7127.
- Adam Vogel, Max Bodoia, Christopher Potts, and Daniel Jurafsky. 2013. Emergence of Gricean maxims from multi-agent decision theory. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1072–1081, Atlanta, Georgia. Association for Computational Linguistics.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Ed Chi, Quoc Le, and Denny Zhou. 2022. Chain of thought prompting elicits reasoning in large language models. arXiv preprint arXiv:2201.11903.
- Wei Wei, Quoc Le, Andrew Dai, and Jia Li. 2018. Air-Dialogue: An environment for goal-oriented dialogue research. In *Proceedings of the 2018 Conference on*

Empirical Methods in Natural Language Processing, pages 3844–3854, Brussels, Belgium. Association for Computational Linguistics.

Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. 2022. React: Synergizing reasoning and acting in language models. *arXiv preprint arXiv:2210.03629*.

A Environment Details

Optimization Each cell of the $k \times k$ table of reviewer-paper affinity scores is sampled from Uniform[0, 100]. To ensure that communication is necessary to do well, we reject a random game unless the optimal score with the agents' pooled knowledge is ≥ 1.25 times as good as the score that either player would achieve with their own information if they impute the average value for unknown cells. We scale values by a random scale sampled from Uniform[1, 10]. The table size k = 8 in our experiments and data collection.

Planning To generate contexts for the dialogue, we create a seed list of 39 site names and locations. Each site is one of the following categories: restaurants, bars, cafes, sights (museums and landmarks), outdoor (parks), or shopping.

On every environment instance, we randomly shuffle the locations of the sites and randomize their features. Each site has five nonzero random features, out of the following list (some of which only apply to some categories:

- Rating (categorical)
- Has parking (bool)
- Has takeout (bool) [restaurants only]
- Touristy (bool)
- Cuisine (categorical) [restaurants only]
- Good for kids (bool) [restaurant, cafe, museum, landmark, park, shop only]
- Accepts reservations (bool) [restaurants only]
- Open late (bool)
- Good for groups (bool)
- Ambience (categorical) [restaurant, cafe, bar]
- Outdoor seating (bool) [restaurant, cafe, bar]
- Vegetarian options (bool) [restaurant, cafe]
- Vegan options (bool) [restaurant, cafe]
- Live music (bool) [restaurant, bar]
- Has Wi-Fi (bool) [cafe]
- Alcohol type (categorical) [bar]
- Viewpoint (bool) [park]

We procedurally generate preferences from the user from the following types:

- Feature: a preference over the value of one of the features above
- Want to go: a preference to go to a specific event or set of events
- Price: a preference to keep the budget less than some fixed amount
- At least one site of type: a preference to go to at least one site of some type (e.g., to visit at least one museum)

• Distance: a (negative) preference per unit traveled between sites

Each of these preferences is parameterized and randomized on every environment instance. Every user has a price and distance preference; the other preferences are sampled with some probability up to a total of P preferences (P = 10 in our experiments and data collection). We specifically exclude preference configurations that are un-intuitive from generation (e.g., a preference for places that do not have takeout). We template natural language descriptions for each preference to present to the user.

A.1 Mediation

On each environment instance, we generate a random calendar for each user by iterating through a 3-day period and generating a 30 min, 60 min, 2 hour, and 4 hour event with probability p_{event} $f_{\text{(shared of these events are selected to be shared$ events that both the assistant and user can see; theremainder are private events that only the user cansee. The importance of each event is sampled fromUniform[1, 10].

We generate a set of F flights for each user with a random start time in the 3-day period, sampling a duration (in hours) from Uniform[1, 10]. Flight prices for each user i are sampled from $\mathcal{N}(\mu_i, \sigma_i)$ to ensure that flight prices a user sees are realistically around the same value, and the parameters of the distribution $\mu = \sigma$ are sampled from Uniform[50, 1000].

We generate a price preference weight $\theta_{\text{price}} \sim \text{Uniform}[1, 20]$ and (negative) preference per hour difference in arrival between the two users' flights $\theta_{\text{arrival}} \sim \text{Uniform}[1, 10]$.

We set $p_{\text{event}} = 0.35$, $f_{\text{shared}} = 0.75$, F = 30 in our experiments and data collection.

B Data Collection Details

Human players from Mechanical Turk were vetted via a pre-qualification survey and data collection was run in multiple dyads, with high-quality players from each dyad being invited to participate in followup rounds of data collection. Workers are informed of the best or average score in the game before starting, and are bonused up to \$2.00 in tiers by how close they get to the best proposal.

Travel Planning - CVID consist, solar setting places would be been - prefer region above 1.3 - of the channes whitegins, house, reseat, like - of 'i like channes, whitegins, house, reseat, like - speaking, area; setting, traves	subtr Entranzi proc 13/0 port for this than ansatzer ansatzer thomage that thomage that	Gos Sant Propositi
 - vould be great if everything is reservable in advance - group of 7, best if we could go to places good for groups - like dray places - definitely was to there out ban's recommendations Roubt Graden, Lincoln Park 	agenti Stating: new game Agent made a proposal	There yer days there are a second to the se
 resting a car so preferably places with parking - back oot live music! - minimize travel distance 	Mad Secul Estimated price S70	Consider the Constant and Const
Scorecard	accepts restrations the hap advice that good for groups the vegetarian potent lake open lain take	SauUs Hurror 2010express Territoriant Entrandi proc 1940
PIOE 2425 Checking which wishint items are satisfied by this itensen; the construction of the set		and tasks daup angen fan angen Fan angen fan a
27 Total travel distance score		propipa Crawneeto
Overall score -22	people for later than experiments for the experiments of the experiments of the open later than gend for groups take	

(a) User view.

(b) Assistant view.

Figure 7: UIs for human players in the Planning task. The user observes a travel planning document with their preferences listed in natural language, but initially no sites. The assistant observes a map of locations and detailed views of their features. The assistant can send a proposed itinerary in their interface, at which point the user observes the set of sites in their itinerary with their features, as well as a score breakdown.



(a) User view.

(b) Assistant view.

Figure 8: UIs for human players in the Mediation task. Each user observes their own work and personal calendars with meeting importances, and their available flight options. The assistant observes both calendars and available flights but not the user's event importances. As shown in the user view, When the assistant proposes a flight, it appears on the user's calendar and the user observes the score breakdown for that proposal.

B.1 Interface Screenshots

The interfaces for the human users and assistants during data collection can be seen in Figure 9 (Matching), Figure 7 (Planning), and Figure 8 (Mediation). Human users and assistants see the same underlying information as models in the environment, presented in an interactive graphical user interface.



Figure 9: UIs for both players in the Optimization task. Both players observe a subset of reviewer-paper affinities in a spreadsheet table. They can send proposals by clicking on cells in the table, at which point the proposal appears in the other player's table.

	Optimization		Planning		Mediation	
	# words (μ)	Score (μ)	# words (μ)	Score (μ)	# words (μ)	Score (μ)
Human Self-Play	176.8 ± 11.4 145.5 ± 3.6	0.92 ± 0.01 0.59 ± 0.02	143.3 ± 6.6 211.2 ± 5.9	0.89 ± 0.01 0.65 ± 0.01	119.0 ± 5.7 233.3 ± 5.12	0.97 ± 0.00 0.81 ± 0.01

Table 1: Comparison of mean scores and dialogue lengths between the human and self-play games, with standard error of the mean. Humans obtain higher scores than language models on all three domains, using significantly fewer messages on both the Planning and Mediation tasks. 8/114 dialogues in Planning did not terminate within 30 messages (15 per player) and 22/162 dialogues in Mediation did not terminate within 45 messages. These were excluded from the results. These results correspond to the data in Figure 4.

	Dialogues	Messages (μ)	Words (μ)	Proposals (μ)	Time (μ)
Optimization	134	18.4 ± 1.1	169.3 ± 10.9	1.7 ± 0.1	8m 9s
Planning	114	9.0 ± 0.4	141.9 ± 6.5	3.0 ± 0.1	10m 56s
Mediation	162	12.8 ± 0.5	119.0 ± 5.7	2.8 ± 0.2	7m 15s
All Domains	409	12.8 ± 0.5	141.8 ± 4.7	2.5 ± 0.1	8m 19s

Table 2: Data statistics for human-human dialogues. We collect a total of 409 dialogues, resulting in 5253 messages and 58K words across domains. Dialogues for each setting are roughly the same number of words on average.

C Experiments

In Table 1 we show the mean and standard error of the mean for the dialogue lengths (in words) and rewards of human-human and self-play games.

D Analysis

We include additional analyses of the humanhuman dialogues. In Table 2, we show additional data statistics for human-human dialogues. In Figure 10, we show the distributions of % of agent words in the dialogues for each task, as a measure of how varied the initiative between users and assistants are in human-human pairs. In Figure 11, we show the time in minutes spent on each dialogue and the corresponding reward of the dialogue. In Figure 12, we show the percentages of messages of each types in our GPT-3 annotation analysis, as described in §7.

E Prompts

During prompted self-play, we bias models to output dialogues that are approximately the same length as the corresponding human-human dialogue by prompting it with "You must make your best final proposal now." when the length of the ongoing dialogue is within 25 words of the human dialogue, and automatically accepting the outputted proposal.

On the subsequent pages, we show the prompts

used to prompt user and assistant in our experiments. The few-shot examples are actual humanhuman dialogues in the dataset, with additional observations on proposals (i.e., the score breakdown) presented in text format. In Planning, we additionally manually augment the prompt example with [think] for both the user and assistant, and [search] steps with example searches and their results. In self-play, models generated from these prompts directly. In prompted self-play, the prefix of a human-human dialogue was appended to these prompts and models continued the dialogue to completion from there.

We also show an example prompt for the query executor in Planning. The database is different on every game instance; during evaluation, we prompt the query executor with the actual database of events for that instance along with the example searches. When the assistant model generates [search] message and query, we add this to the query executor prompt and generate a result, which then is returned to the assistant model.



Figure 10: Our tasks involve *mixed initiative* between users and assistants. In this figure, we show histograms representing the percent of words which were sent by the *assistant* role in each game. Because roles in Optimization are symmetric, we plot the percent of words sent by the second agent, which is roughly 50% on average. In Planning, users typically send more words than assistants do, in order to share constraints and comment on proposals. In Mediation, which involves two users and one assistant, assistants send roughly one third of messages on average.



Figure 11: Percent of total score as a function of time to complete the game in human-human dialogues. There is a weak correlation between completion time and score, with the longest dialogues typically being near the maximum possible score. However, many human-human players are capable of reaching the maximum score in all three tasks within a short amount of time (e.g., < 5 minutes). Across tasks, the median game length is 8min 55sec.



Figure 12: Percent of message types in human-human dialogues. Exchanging information is a key aspect of decision-oriented dialogue: *share* and *query* messages are the most common message types for all three tasks.

You and your partner are area chairs for a conference and you have to assign reviewers to papers. Each of you has some information about which reviewers would be good for which papers, but you'll have to communicate in order to make the best assignments. For each game, you will see a table of reviewer-paper similarity scores. The higher the score, the better the fit. You will also see a list of reviewers and papers. You can send messages to your partner, propose assignments, and accept or reject your partner's proposals. Your goal is to propose a one-to-one matching between reviewers and papers with the highest sum of scores. The "Final Score" at the end of the chat is out of 1.0 and shows how well you did relative to the best you could do with your partner. Your goal is to maximize that score. EXAMPLE 1. Reviewer Paper Similarity Scores: ,BLEU: a Method for Automatic Evaluation of MT,Electra: Pre-training Text Encoders as Discriminators,GloVe: Global Vectors for Word Representation, GLUE: A Multi-Task Benchmark and Analysis Platform for NLU, LLaMA : Open and Efficient Foundation Language Models,RoBERTa: A Robustly Optimized BERT Pretraining Approach ,QuAC: Question Answering in Context,SWAG: An Adversarial Dataset for Commonsense Inference Ava Li,,,167,,,,431 Daniel Nguyen,236,,459,,,,213,83 Sofia Patel,,,171,106,255,, Andrei Petrov,60,,13,,,,306,320 Morgan Reed,,,,,,,162, Joseph Santos,190,,,18,,,, Ethan Smith, 204,13,325,,,, Noah Wilson,,,185,,,,380,283 You: [message] Hello! Partner: [message] Hi! Who should we put for SWAG? You: [message] I think Ava LI would be good for Swag? Partner: [message] Sounds good to me!~ You: [message] I also think Daniel Nguyen woould be good for GloVe if you haven't allocated him yet. Partner: [message] What do you have for LLaMA? I don't have anything for LLaMA. You: [message] $ar{I}$ only have limited information on LLaMA. Sofia Patel might ve a good candidate for it. / Ethan might good for GLUE maybe? / BLEU I don't much information on, but Joseph has a decent score in that field. Partner: [message] I have a really high score for GLUE with Andrei so I am going to keep that one. You: [message] Who you think would be good for Electra? Partner: [message] Sofia Patel is the best option for that category on my end. You: [message] I don't have much information on Morgan Reed or Ethan Smith, how about you? Partner: [propose] Proposal:
  - BLEU: Morgan Reed
br/>  - Electra: Sofia Patel
br/>  GLUE: Andrei Petrov
br/>  - GloVe: Daniel Nguyen
br/>  - LLaMA: Ethan Smith
br/>  - QuAC
: Noah Wilson
br/>  - RoBERTa: Joseph Santos
br/>  - SWAG: Ava Li You: [accept] Final Score: 1 EXAMPLE 2 Reviewer Paper Similarity Scores: ,BLEU: a Method for Automatic Evaluation of MT,Electra: Pre-training Text Encoders as Discriminators,GloVe: Global Vectors for Word Representation, GLUE: A Multi-Task Benchmark and Analysis Platform for NLU, LLaMA : Open and Efficient Foundation Language Models, RoBERTa: A Robustly Optimized BERT Pretraining Approach ,QuAC: Question Answering in Context,SWAG: An Adversarial Dataset for Commonsense Inference Ava Li,386,,,120,144,,,202 Daniel Nguyen,,,,434,,,, Sofia Patel, 439, ,, 38, ,, 270 Andrei Petrov, ,, 169, 294, 231, ,101, Morgan Reed, 14, 144, ,, 478, ,, Joseph Santos, 251, 115, ,, ,275, 154, Ethan Smith, 86,, 19,, 19,,, 57 Noah Wilson,,,,159,313,,,188 Partner: [message] I am not 10/10 confident on anyone, but lots solid options on my end. Id say my most confident lock in would be Sofia on LLaMA based on what im seeing. Ethan on Glue looks great as well / Ava is above average on BLEU and Glove You: [message] Okay, give me a second / so Sofia on LLama / Morgan for me is the BEST on Llama / they have the best pairing of all my info Partner: [message] hmm, looks like we have a lot of good options for Llama in that case. Maybe we come back to that. I have a ton of info for quac, the only person I dont know about quac is Joseph. But otherwise , Ethan or Ava is the best at it / Though nobody is great at it to be honest. You: [message] I have only who is bad at Quac so we can go with who you'd like / Joseph and Andei are 100% out in that category / Let me know if you lock someone in there for now / Canwe lock Daniel into Glue / he is really strong choice there
Partner: [message] That works for me, that lets me put Ethan onto quac in that case / Do you have andrei as
being solid at anything? All I see is that he is kinda good at Glue, but he might be a candidate for taking a gamble You: [message] Andrei is mid at Glue / but not worth taking over Daniel Partner: [message] Ok, sounds good You: [message] Sofia is killing it for Bleu / Better than Ava who is also really good Partner: [message] Hmmm, Sofia is my strongest candidate for Llama, its my most confident pick out of all my

- info. / but, I do see other options for Ava so maybe its worth it / would you say 9 or 10 out of 10 on Sofia on BLEU?
- You: [message] Is Sofia better than Morgan on Llama / if so we can move Sofia / but Morgan is my best for his Llama knoweldge

Partner: [message] Hmmm. Joseph is solid at Llama as well. And I dont have any other info for Joseph. so I kinda like him there. But I also dont have any other good spots for Morgan, so maybe we roll with that for now. / Do you have any info on who would be a good candidate for roberta at all? / or swag. I got nothing on those, might need to take some risk You: [message] Joseph is alright barely

Partner: [message] And what about electra? / I only know bad options for those three. You: [message] I got Morhan and Jo bad at Electra / do you have enough to fill in the rest Partner: [message] I got ava and Noah bad at electra / might put andrei there? You: [message] Andrei for now agreed / is Jo just Roberta for now

Partner: [message] gonna throw out a proposal but definitely reject if you see something / I have him on

Partner: [message] gonna throw out a proposal but definitely reject if you see something / I have him on swag right now but maybe roberta better? I have no info either way Partner: [propose] Proposal:
br/>  - BLEU: Sofia Patel
br/>  - Electra: Andrei Petrov
br/>  - GLUE: Daniel Nguyen
br/>  - GloVe: Ava Li
br/>  - LLaMA: Morgan Reed
br/>  - QuAC: Ethan Smith
br/>  - RoBERTa: Noah Wilson
br/>  - SWAG: Joseph Santos

You: [reject]

You: [message] Thats actually really good / yeah that works / if you want to re propose / I dont see anything clearly off

Partner: [message] Its scary on my end because almost every person I have locked in has no info on my end haha / its almost all you but Im still fairly confident since none of my scores were insane

GLUE: Daniel Nguyen
br/>  - GloVe: Ava Li
br/>  - SWAG: Joseph Santos

You: [accept] Final Score: 1

EXAMPLE 3.

Planning: Assistant Prompt

You are a travel agent. Book a set of three destinations that make the user most happy. Your objective is to maximize the "Final Score" at the end of the chat, which scores how well the final itinerary you proposed matches the user's preferences. You can use the `Search` tool with the following API: field: can be name, category, price, info, or any other field of an site category: can be [restaurant, cafe, museum, bar, landmark, park, shop] Search: Parameters - fields: list of field names to return - filters: list of filters to intersect with AND. Can only filter one of the fields above. - text_query: freeform text query to search in event descriptions. Will be intersected with filters with AND sort_by: list of fields or callable function to sort results by. - limit: number of results to return USER 1. User: [message] I'd like to see some live music, eat only takeout from Korean, kosher, Japanese or seafood restaurants. Vegan options are a plus and I'd like to stop by Mad Seoul. I'd also like places with parking, good city views and kid friendly. My budget is \$30. You: [think] The user listed many preferences. I will see what the options are for some of them, and try to suggest an event that satisfies many of their preferences at once. You: [tool] Search(fields=[name], text_query=good for kids) Search Results (6): name Saul's The Dockside Grill Riverside Trail Moabit Garden Common Grounds The Dive You: [tool] Search(fields=[name], text_query=viewpoint) Search Results (2): name Garden of Wonders Moabit Garden You: [tool] Search(fields=[name], text_query=has parking) Search Results (3): name Liberty Memorial Common Grounds Lincoln Park You: [think] Common Grounds is good for kids and has parking, so it seems like an option the user might like Let me send a partial proposal so ${\tt I}$ can see what the user thinks. You: [propose] [Common Grounds, NULL, NULL] You: [message] I have made a proposal. Please let me know what you think of it. User: [message] It's not bad so far, I'd really like to stop by Mad Seoul though. You: [message] Sure. I can help you out with that! Are there any other events you'd like to go to after Mad Seoul? User: [message] I'd like to go to see some live music. You: [think] I will try to find somewhere with live music near Mad Seoul and check whether the event also satisfies the other preferences the user listed. You: [tool] Search(fields=[name, good for kids, has parking, viewpoint], text_query=live music, sort_by=[distance_to(Mad Seoul)]) Search Results (1): name|category|good for kids|has parking|viewpoint|distance_to(Mad Seoul) Cookies Cream|restaurant|False|True|False|1.2 You: [message] I have one option for you that you might be interested in. However, it is not recommended for kids. Are there any other places? User: [message] Somewhere with a panoramic view of the city would be nice or somewhere that's kid-friendly in general. You: [tool] Search(fields=[name, category, good for kids, has parking, viewpoint], filters=[good for kids OR viewpoint], sort_by=[distance_to(Mad Seoul)]) Search Results (4): name|category|good for kids|has parking|viewpoint|distance_to(Mad Seoul) Atlas Park|park|True|True|False|0.2 Lincoln Park|park|True|False|False|0.8 Moabit Garden|park|False|True|True|1.3 Garden of Wonders|park|False|False|True|1.8 You: [message] I have several options available. Do you have a price point? [message] As long as it's \$30 or under, it should be fine. User: You: [tool] Search(fields=[name, category, good for kids, has parking, viewpoint], filters=[good for kids OR viewpoint], sort_by=[distance_to(Mad Seoul), price]) Search Results (4): name|category|good for kids|has parking|viewpoint|distance_to(Mad Seoul)|price Atlas Park|park|True|True|False|0.2|0 Lincoln Park|park|True|False|False|0.8|0 Moabit Garden|park|False|True|True|1.3|0

Garden of Wonders|park|False|False|True|1.8|0

You: [propose] [Mad Seoul, Lincoln Park, Atlas Park]

You: [message] I have found several options. If you have enough time you may even be able to go to all of these places as they are all under 2 miles away from each other and close to Mad Seoul. Both parks are also kid friendly. User: [reject]

User: [message] It would be great if you could significantly lower the travel time. Maybe another restaurant or a concert that's closer?

You: [think] Concert is not a category I can search by. I should look for a restaurant that is close to Mad Seoul and satisfies the user's preferences as much as possible.

You: [tool] Search(fields=[name, price, info], filters=[category == restaurant], sort_by=[distance_to(Mad Seoul)])

Search Results (4): name|price|info|distance_to(Mad Seoul)

Caribbean Corner|10|divey, has takeout, live music, vegetarian options|0.0 El Toro Steakhouse|130|good for groups, live music, outdoor seating|0.8

Earthbar|40|classy, rating: 3, vegan options|0.9 Saul's|40|spanish, touristy|0.9

You: [message] Mad Seoul is 0.8 miles away from Lincoln Park. I can definitely find a restaurant for you. Do you want a place with live music, touristy, kid-friendly, and has vegetarian options? The price point is around \\$10.

User: [message] Yes, all those things would be great. Just make sure to keep the travel distance as low as you can get it.

You: [propose] [Mad Seoul, Lincoln Park, Caribbean Corner]

You: [message] I have several options. One option might be a little too far for you, however it does have live music. I also have another restaurant that is closer. All of the places I have recommended are less than a mile apart from each other. User: [reject]

User: [message] The places you've chosen are great, but everything is still too far apart for me. Choose the places closest to each other if you can. You: [think] I should just look for the closest places to Mad Seoul.

You: [tool] Search(fields=[name], sort_by=[distance_to(Mad Seoul)], limit=2)

Search Results (2):

name|distance_to(Mad Seoul)

Caribbean Corner 0.0 Hindenberg Memorial |0.2

You: [propose] [Mad Seoul, Caribbean Corner, Hindenberg Memorial] You: [message] Yes sir, but there are only so many options that are kid friendly near the cafe of your choice. However I have one more proposal that is within a much better distance of each other. User: [accept]

FINAL SCORE: 92/100

USER 2.

Planning: User Prompt

```
You are traveling to a new city and consulting a travel agent. For each city, you have created a document listing things you would like to do and preferences about the places you visit. The preferences are not
       shared between cities. Communicate with the travel agent to find the best destinations to go to for
      the day.
Your objective is to maximize the "Final Score" at the end of the chat, which scores how well the itinerary
     you agreed on matches your preferences.
CITY 1.
Travel Preferences:
check out live music!
prefer just eating takeout
keep budget below $30
would be great if everything is reservable in advance
like: korean, kosher, japanese, seafood
generally like eating vegan options
definitely want to go to Mad Seoul
renting a car so preferably places with parking
would love to see some panoramic views of the city family trip, best to go to places that are good for kids
minimize travel distance
You: [message] I'd like to see some live music, eat only takeout from Korean, kosher, Japanese or seafood restaurants. Vegan options are a plus and I'd like to stop by Mad Seoul. I'd also like places with parking, good city views and kid friendly. My budget is $30.
Agent: [propose] [Common Grounds, NULL, NULL]
Proposal Score:
1) (score: 4) Common Grounds
good for groups: True
open late: False
rating: 2.5
touristy: False
vegan options: True
2) Empty
3) Empty
4) Empty
5) Empty
Overall Checklist:
YES (score: 0) keep budget below $30
NO (score: -9) definitely want to go to Mad Seoul
TOTAL SCORE: +4+0+0+0+0+0=-5
Agent: [message] I have made a proposal. Please let me know what you think of it.
You: [message] It's not bad so far, I'd really like to stop by Mad Seoul though.
Agent: [message] Sure. I can help you out with that! Are there any other events you'd like to go to after
     Mad Seoul?
You: [message] I'd like to go to see some live music.
Agent: [message] I have one option for you that you might be interested in. However, it is not recommended for kids. Are there any other places?
You: [message] Somewhere with a panoramic view of the city would be nice or somewhere that's kid-friendly in
      general.
Agent:
        [message] I have several options available. Do you have a price point?
You: [message] As long as it's $30 or under, it should be fine.
Agent: [propose] [Mad Seoul, Lincoln Park, Atlas Park]
Proposal Score:
1) (score: 1) Mad Seoul
good for kids: False
live music: False
open late: True
touristy: True
vegan options: True
2) (score: -8) Travel from Mad Seoul to Lincoln Park, 0.8mi
3) (score: -3) Lincoln Park
good for groups: False
good for kids: True
rating: 3
touristy: False
viewpoint: False
4) (score: -11) Travel from Lincoln Park to Atlas Park, 1.1mi
5) (score: 7) Atlas Park
good for groups: False
good for kids: True
has parking: False
touristy: True
viewpoint: True
Overall Checklist:
NO (score: -1) keep budget below $30
YES (score: 9) definitely want to go to Mad Seoul
TOTAL SCORE: +1-8-3-11+7-1+9=-6
You can [think], or output one of these choices:
(1) [accept]
(2) [reject]
```

Agent: [message] I have found several options. If you have enough time you may even be able to go to all of these places as they are all under 2 miles away from each other and close to Mad Seoul. Both parks are also kid friendly. You: [think] I am losing the most points from the travel time between events. I should reject the proposal and tell the agent to find sites that are closer to each other. You: [reject] You: [message] It would be great if you could significantly lower the travel time. Maybe another restaurant or a concert that's closer? Agent: [message] Mad Seoul is 0.8 miles away from Lincoln Park. I can definitely find a restaurant for you. Do you want a place with live music, touristy, kid-friendly, and has vegetarian options? The price point is around \$10. You: [message] Yes, all those things would be great. Just make sure to keep the travel distance as low as vou can get it. Agent: [propose] [Mad Seoul, Lincoln Park, Caribbean Corner] Proposal Score: 1) (score: 1) Mad Seoul good for kids: False live music: False open late: True touristy: True vegan options: True 2) (score: -8) Travel from Mad Seoul to Lincoln Park, 0.8mi
3) (score: -3) Lincoln Park good for groups: False good for kids: True rating: 3 touristy: False viewpoint: False 5) (score: -8) Travel from Lincoln Park to Caribbean Corner, 0.8mi 5) (score: -1) Caribbean Corner ambience: divey good for groups: False good for kids: False has takeout: True live music: True Overall Checklist: NO (score: -1) keep budget below \$30 YES (score: 9) definitely want to go to Mad Seoul TOTAL SCORE: +1-8-3-8-1-1+9=-11 You can [think], or output one of these choices: (1) [accept] (2) [reject] Agent: [message] I have several options. One option might be a little too far for you, however it does have live music. I also have another restaurant that is closer. All of the places I have recommended are less than a mile apart from each other. You: [think] I am still losing a lot of points from the travel time between events. This seems more important to me than the other features of the sites. You: [reject] You: [message] The places you've chosen are great, but everything is still too far apart for me. Choose the places closest to each other if you can. Agent: [propose] [Mad Seoul, Caribbean Corner, Hindenberg Memorial] Proposal Score: 1) (score: 1) Mad Seoul good for kids: False live music: False open late: True touristy: True vegan options: True 2) (score: 0) Travel from Estimated Travel to Caribbean Corner, $0\mbox{mi}$ 3) (score: -1) Caribbean Corner ambience: divey good for groups: False good for kids: False has takeout: True live music: True 4) (score: -2) Travel from Estimated Travel to Hindenberg Memorial, 0.2mi 5) (score: -2) Hindenberg Memorial good for groups: True good for kids: False open late: False rating: 5 touristy: True Overall Checklist: NO (score: -1) keep budget below \$30 YES (score: 9) definitely want to go to Mad Seoul TOTAL SCORE: +1+0-1-2-2-1+9=4 You must output one of these choices: (1) [accept]
(2) [reject] Agent: [message] Yes sir, but there are only so many options that are kid friendly near the cafe of your

choice. However I have one more proposal that is within a much better distance of each other. You: [think] All the events are very close to each other and the score is a lot better. My total score seems like it could be pretty good. I should accept this proposal. You: [accept] FINAL SCORE: 92/100

CITY 2.

Database:

name': 'Taqueria y Mas'}
{'est_price': 20, 'etype': 'bar', pe': 'bar', 'features': {'ambience': 'intimate', 'good for groups': False 'live music': False, 'outdoor seating': False}, 'loc': [-122.26, 37.87], 'good for groups': False, 'has parking': False, 'name': ' Bards n Brews'} {'est_price': 350, 'etype': 'shop', 'features': {'good for groups': True, 'good for kids': False, 'has parking': False, 'open late': False, 'touristy': True}, 'loc': [-122.26, 37.87], 'name': 'Vista Ridge Mall'}
{'est_price': 10, 'etype': 'restaurant', 'features': {'accepts reservations': False, 'has parking': True, '
 has takeout': False, 'open late': False, 'vegetarian options': False}, 'loc': [-122.3, 37.88], 'name':
 'El Toro Steakhouse'}
{'est_price': 30, 'etype': 'bar', 'features': {'good for groups': True, 'has parking': False, 'live music':
 True, 'rating': 2, 'touristy': False}, 'loc': [-122.26, 37.84], 'name': 'Kozy Kar'}
{'est_price': 5, 'etype': 'cafe', 'features': {'has parking': False, 'outdoor seating': True, 'touristy':
 True, 'vegan options': False, 'vegetarian options': True}, 'loc': [-122.26, 37.87], 'name': 'The
 Guncote Rar'} Mall'} Cupcake Bar'} {'est_price': 100, 'etype': 'restaurant', 'features': {'accepts reservations': False, 'ambience': 'serious', 'good for kids': True, 'has parking': True, 'live music': True}, 'loc': [-122.26, 37.84], 'name': "
Saul's"
{'est_price': 150, 'etype': 'restaurant', 'features': {'accepts reservations': False, 'good for groups':
True, 'has parking': True, 'open late': False, 'outdoor seating': True}, 'loc': [-122.27, 37.87], 'name
': 'Caribbean Corner'}
{'est_price': 0, 'etype': 'park', 'features': {'good for groups': False, 'has parking': True, 'open late':
True, 'rating': 4.5, 'touristy': False}, 'loc': [-122.29, 37.88], 'name': 'Moabit Garden'}
{'est_price': 50, 'etype': 'restaurant', 'features': {'ambience': 'casual', 'good for groups': True, 'has
parking': False, 'has takeout': False, 'rating': 4.5}, 'loc': [-122.27, 37.89], 'name': "Lucia's"}
{'est_price': 60, 'etype': 'bar', 'features': {'ambience': 'casual', 'good for groups': True, 'live music':
True, 'outdoor seating': True, 'touristy': True}, 'loc': [-122.3, 37.89], 'name': 'A-Trane'}
{'est_price': 60, 'etype': 'bar', 'features': {'ambience': 'casual', 'good for groups': False, 'has parking
': True, 'open late': False, 'touristy': True}, 'loc': [-122.3, 37.89], 'name': 'A-Trane'}
{'est_price': 0, 'etype': 'landmark', 'features': {'good for groups': False, 'has parking': True, 'open late
': True, 'rating': 1.5, 'touristy': True}, 'loc': [-122.26, 37.87], 'name': 'Hindenberg Memorial'}
{'est_price': 0, 'etype': 'park', 'features': {'good for groups': False, 'has parking': True, 'open late':
False, 'touristy': True}, 'loc': [-122.27, 37.87], 'name': 'The Arboretum'}
{'est_price': 0, 'etype': 'park', 'features': {'good for groups': False, 'has parking': True, 'open late':
False, 'touristy': True, 'icate', 'features': {'good for groups': False, 'has parking': True, 'open late':
False, 'touristy': True}, 'loc': [-122.27, 37.87], 'name': 'The Arboretum'}
{'est_price': 15, 'etype': 'cafe', 'features': {'good for groups': False, 'has parking': True, 'open late':
False, 'touristy': True, 'reatines': {'good for groups': False, 'anbience': 'trendy', 'good for groups': Fals good for kids': True, 'has parking': True, 'live music': True}, 'loc': [-122.26, 37.84], 'name':

Cafe'}

{'est_price': 50, 'etype': 'restaurant', 'features': {'accepts reservations': False, 'ambience': 'classy' cuisine': 'seafood', 'good for groups': False, 'open late': True}, 'loc': [-122.27, 37.88], 'name': Mad Seoul'}

{'est_price': 110, 'etype': 'restaurant', 'features': {'has parking': True, 'open late': True, 'outdoor seating': False, 'touristy': True, 'vegetarian options': True}, 'loc': [-122.27, 37.87], 'name': ' Earthbar'}

Earthbar'}
{'est_price': 0, 'etype': 'museum', 'features': {'good for groups': False, 'has parking': False, 'open late
 ': True, 'rating': 5, 'touristy': True}, 'loc': [-122.29, 37.89], 'name': 'City Museum of Art'}
{'est_price': 40, 'etype': 'bar', 'features': {'ambience': 'casual', 'live music': False, 'open late': False
 , 'outdoor seating': False, 'rating': 1.5}, 'loc': [-122.28, 37.89], 'name': 'The Jazz Spot'}
{'est_price': 0, 'etype': 'landmark', 'features': {'good for groups': True, 'good for kids': False, 'has
 parking': False, 'open late': True, 'touristy': True}, 'loc': [-122.24, 37.87], 'name': 'The Tower'}
{'est_price': 40, 'etype': 'museum', 'features': {'good for groups': True, 'good for kids': False, 'open late
 ': True, 'rating': 5, 'touristy': False}, 'loc': [-122.26, 37.87], 'name': 'BAMPFA'}
{'est_price': 90, 'etype': 'shop', 'features': {'good for groups': True, 'good for kids': True, 'has parking
 ': True, 'open late': False, 'rating': 3}, 'loc': [-122.26, 37.87], 'name': 'Market Street'}
{'est_price': 0, 'etype': 'landmark', 'features': {'good for groups': False, 'good for kids': True, 'has
 parking': False, 'open late': False, 'rating': 3}, 'loc': [-122.26, 37.87], 'name': 'Market Street'}
{'est_price': 0, 'etype': 'landmark', 'features': {'good for groups': False, 'good for kids': True, 'has
 parking': False, 'open late': False, 'rating': 3}, 'loc': [-122.26, 37.87], 'name': 'Market Street'}
{'est_price': 0, 'etype': 'landmark', 'features': {'good for groups': False, 'good for kids': True, 'has
 parking': False, 'open late': True, 'touristy': False}, 'loc': [-122.26, 37.86], 'name': 'Liberty
 Memorial'} Memorial'}

Society'} {'est_price':

Lprice': 10, 'etype': 'landmark', 'features': {'good for groups': True, 'good for kids': True, 'open late': True, 'rating': 4.5, 'touristy': True}, 'loc': [-122.27, 37.87], 'name': "Einstein's summer house"}

{'est_price': 0, 'etype': 'park', 'features': {'good for groups': True, 'has parking': True, 'open late': False, 'rating': 3.5, 'viewpoint': True}, 'loc': [-122.28, 37.89], 'name': 'Garden of Wonders'} {'est_price': 50, 'etype': 'restaurant', 'features': {'accepts reservations': False, 'good for groups': True , 'good for kids': False, 'has takeout': True, 'outdoor seating': True}, 'loc': [-122.26, 37.87], 'name

{'est_price': 50, 'etype': 'restaurant, 'could '' , 'good for kids': False, 'has takeout': True, 'outdoor seating': True}, 'loc : L'12120, could ': 'The Cakery'} {'est_price': 15, 'etype': 'cafe', 'features': {'ambience': 'intimate', 'has parking': False, 'open late': False, 'outdoor seating': False, 'touristy': True}, 'loc': [-122.27, 37.87], 'name': 'Common Grounds'} {'est_price': 400, 'etype': 'shop', 'features': {'good for groups': False, 'has parking': False, 'open late '' False, 'rating': 2.5, 'touristy': True}, 'loc': [-122.28, 37.89], 'name': 'Artisan Street Fair'}

```
'has parking': False, 'vegan options': True, 'vegetarian options': False}, 'loc': [-122.27, 37.87], '
nas parking : False, 'Vegan options : True, 'Vegetarian options : False}, 'loc': [-122.27, 37.87], 'name': 'Cookies Cream'}
{'est_price': 60, 'etype': 'restaurant', 'features': {'good for kids': True, 'has parking': True, 'live
music': True, 'rating': 5, 'touristy': True}, 'loc': [-122.27, 37.87], 'name': 'The Dockside Grill'}
{'est_price': 370, 'etype': 'shop', 'features': {'good for groups': False, 'good for kids': False, 'has
parking': True, 'open late': False, 'touristy': False}, 'loc': [-122.26, 37.87], 'name': 'Central Plaza
       }
'has parking
Ouery: Search(fields=[name], filters=[category == landmark])
Result:
Search Results (4):
name
Hindenberg Memorial
The Tower
Liberty Memorial
Einstein's summer house
Query: Search(fields=[name], filters=[category == concert])
Result:
Search Results: No results
Query: Search(fields=[name], text_query=live music)
Result:
Search Results (6):
name
Bards n Brews
Kozy Kar
Saul's
A-Trane
The Jazz Spot
The Dockside Grill
Query: Search(fields=[name, price], text_query=live music, filters=[price <= 40])</pre>
Result:
Search Results (3):
name|price
Bards n Brews|20
Kozy Kar|30
The Jazz Spot|40
Query: Search(fields=[name, price], filters=[category == restaurant, price <= 10], sort_by=[distance_to(The</pre>
      Mall)])
Result:
Search Results (1):
name|price|distance
El Toro Steakhouse | 10 | 0.8
Query: Search(fields=[name, price, distance], filters=[category == restaurant], sort_by=[distance_to(The
      Mall), price])
Result:
Search Results (10):
name | price | distance
El Toro Steakhouse | 10 | 0.8
Taqueria y Mas|40|3.6
Lucia's|50|1.6
Cookies Cream | 50 | 1.9
Mad Seoul | 50 | 2.2
The Cakery|50|2.8
The Dockside Grill 60 2.0
Saul's|100|3.4
Earthbar | 110 | 2.2
Caribbean Corner | 150 | 2.2
Query: Search(fields=[name], text_query="good for kids", filters=[category == park], sort_by=[distance_to(
      Saul's)])
Result:
Search Results (2):
name|distance
Lincoln Park|1.8
Riverside Trail|2.0
Query: Search(fields=[name], filters=[vegan == true])
Result:
You cannot filter by vegan. Try searching with a text query instead.
```

Mediation: Assistant Prompt

You are a travel agent helping two users, User 0 and User 1, plan a trip together. They are both traveling from different cities but want to arrive at around the same time. Your job is to help mediate by chatting with each user individually and proposing a set of flights that works for both of them. You should try your best to minimize costs, and to avoid missing important meetings. You can see the users' calendars, but you will need to chat with them in order to figure out which meetings are important and which ones they can skip.

Your objective is to maximize the "Final Score" at the end of the chat (max score 1), which scores how well you booked a good flight for each user according to individual and group preferences.

You can send [message] and [propose].

TRIP 1.

```
User 0 Information
Flights:
id | carrier | price | times
0 | JetBlue | 623 | 5/31 12:34 PM - 8:34 PM
1 | Delta | 50 | 5/31 2:23 PM - 10:25 PM
2 | Alaska | 632 | 5/31 4:14 PM - 12:14 AM
3
     American | 803 | 5/31 8:13 PM - 4:13 AM
    Delta | 1299 | 5/31 8:35 PM - 4:36 AM
American | 50 | 6/1 5:57 AM - 1:59 PM
4
5
    United | 50 | 6/1 7:49 AM - 3:49 PM
6
  Т
     Southwest | 2566 | 6/1 10:29 AM - 6:31 PM
7
     Southwest | 50 | 6/1 12:27 PM - 8:27 PM
8
  United | 50 | 6/1 4:36 PM - 12:36 AM
| Delta | 50 | 6/1 4:43 PM - 12:44 AM
| Delta | 421 | 6/1 5:56 PM - 1:56 AM
9
  1
10
11
   | JetBlue | 1202 | 6/2 3:06 AM - 11:06 AM
| JetBlue | 1620 | 6/2 3:20 AM - 11:22 AM
12
13
14 | Alaska | 739 | 6/2 4:37 AM - 12:37 PM
   | Delta | 208 | 6/2 5:07 AM - 1:08 PM
15
16
      JetBlue | 2099 | 6/2 8:02 AM - 4:03 PM
17
      Alaska | 547 | 6/2 9:52 AM - 5:52 PM
18 | Delta | 2817 | 6/2 12:49 PM - 8:49 PM
19 | Alaska | 184 | 6/2 3:25 PM - 11:25 PM
20 | Alaska | 2447 | 6/2 4:00 PM - 12:00 AM
21 | United | 3489 | 6/2 4:18 PM - 12:18 AM
22 | Alaska | 1850 | 6/2 5:52 PM - 1:52 AM
Calendar:
id | times
0 | 6/2 2 PM - 2:30 PM
1 | 6/1 9:30 AM - 10 AM
2 | 6/2 4 PM - 4:30 PM
     5/31 3:30 PM - 7:30 PM
3
  5/31 11:30 AM - 12 PM
4
  | 5/31 9:30 AM - 10:30 AM
5
  | 6/1 5:30 PM - 6 PM
6
  | 6/1 10 AM - 2 PM
7
     6/2 12 PM - 2 PM
8 |
9 | 6/1 9 AM - 9:30 AM
User 1 Information
Flights:
id | carrier | price | times
0 | Delta | 2103 | 5/31 9:33 AM - 12:33 PM
1 | United | 1322 | 5/31 2:22 PM - 5:22 PM
2 | United | 1181 | 5/31 3:27 PM - 6:27 PM
     United | 345 | 5/31 5:00 PM - 8:00 PM
3
    JetBlue | 1217 | 5/31 6:30 PM - 9:30 PM
4
    JetBlue | 50 | 5/31 7:13 PM - 10:14 PM
5
  T
    JetBlue | 882 | 6/1 6:24 AM - 9:24 AM
6
  Т
    United | 469 | 6/1 8:22 AM - 11:22 AM
7
  | American | 518 | 6/1 12:40 PM - 3:40 PM
8
9 | Alaska | 357 | 6/1 3:38 PM - 6:38 PM
10
    | JetBlue | 340 | 6/1 4:41 PM - 7:42 PM
11
   | Southwest | 2017 | 6/2 6:12 AM - 9:12 AM
      Alaska | 1003 | 6/2 10:19 AM - 1:19 PM
12 |
      Southwest | 1456 | 6/2 10:26 AM - 1:26 PM
13
   Delta | 871 | 6/2 10:43 AM - 1:44 PM
14
   Southwest | 2204 | 6/2 1:50 PM - 4:50 PM
15
   American | 1108 | 6/2 2:07 PM - 5:07 PM
16
17
      American | 387 | 6/2 2:29 PM - 5:29 PM
   | Delta | 1617 | 6/2 3:53 PM - 6:53 PM
18
      Southwest | 336 | 6/2 4:29 PM - 7:29 PM
Southwest | 50 | 6/2 5:12 PM - 8:12 PM
19 I
20 |
      Alaska | 779 | 6/2 6:23 PM - 9:23 PM
21
22 | American | 50 | 6/2 6:25 PM - 9:25 PM
Calendar:
id | times
0 | 6/1 5:30 PM - 6 PM
1 | 6/1 3 PM - 3:30 PM
2 | 5/31 5 PM - 7 PM
3 | 6/1 7 PM - 9 PM
```

4 | 6/2 9 AM - 1 PM 5 | 6/1 9 AM - 1 PM 6 | 6/2 4 PM - 6 PM 7 | 6/2 6 PM - 7 PM 8 | 5/31 8:30 PM - 9:30 PM 9 | 6/1 1:30 PM - 2:30 PM 10 | 5/31 9:30 AM - 11:30 AM User 1: [message] Alright, I need to book a flight, what do you have that if affordable between 5/31 and 6/2 at my local airport? You to 0: [message] Hello! I hear you would like to set up a flight! Does 6/2 @ 184\$ sound good? You to 1: [message] Hello! Does 6/2 @ 387\$ work for you? User 0: [message] Do you know what time this would be at? / If you have cheap flights on 6/2 I would prefer to have it after 7 PM, if possible You to 1: [message] Or we have a flight on 6/2 for \$50 that lands at 9:25? User 1: [message] I will miss a little bit of a meeting, but that is super affordable. Lets take a look at that one User 0: [message] I have a gap as well on 5/31 from 12pm until 3 $\ensuremath{\text{PM}}$ You to 0: [message] Unfortunately, all the flights after 7PM are in the higher price range. There is a flight that leaves at 5:52PM @ \$1850 if that is more appropriate? You to 1: [message] Sounds good! I will send it over momentarily! You to 0: [message] Unfortunately, there are no flights before 3PM on 5/31. User 0: [message] Due to the high price and a medium important personal meeting I have at 5:30 PM, I don't think that would be the best option for me. Could we try something after 6 PM on 6/1?You to 0: [message] I have found a flight that leaves 5:56PM on 6/1 for \$421 if that works for you? You to 1: [message] How does 6/1 arriving at 7:42 for \$340 work for you? User 1: [message] Can you pull up that proposal for me? You to all: [propose] user 0: id 11, user 1: id 10 Flight for user 0: 11 | Delta | 421 | 6/1 5:56 PM - 1:56 AM Flight for user 1: 10 | JetBlue | 340 | 6/1 4:41 PM - 7:42 PM User 1: [reject] You to 1: [message] Sending the proposal now! User 0: [reject] User 1: [message] What about Friday? You to 1: [message] How does 6/2 work on 6:25PM for \$50? User 1: [message] Sure lets take a look at that You to all: [propose] user 0: id 22, user 1: id 22 Flight for user 0: 22 | Alaska | 1850 | 6/2 5:52 PM - 1:52 AM Flight for user 1: 22 | American | 50 | 6/2 6:25 PM - 9:25 PM User 0: [reject] User 1: [reject] You to all: [propose] user 0: id 19, user 1: id 22 Flight for user 0: 19 | Alaska | 184 | 6/2 3:25 PM - 11:25 PM Flight for user 1: 22 | American | 50 | 6/2 6:25 PM - 9:25 PM User 0: [accept] You to 0: [message] How does 6/2 for \$1850 for 5:52PM - 1:52PM sound? User 1: [accept] User 0: [message] Thanks that worked a lot more for me! Final Score: 1 TRIP 2.

You are planning a reunion with your friend in a new city! You are flying in from different states and trying to book a flight that arrives around the same time.

- You've got a busy schedule of remote meetings and want to make sure your flight doesn't conflict with any of those meetings, but you also want to arrive as close to the same time as your friend as possible. You' d also like to keep costs low, and some of your meetings are more important than others.
- To help organize the trip, you will chat with a travel agent who has access to you and your friend's work calendars and the set of flights. The agent doesn't have access to your personal calendar or know how important your meetings are, so you'll need to chat with them to share this information. This agent will also be talking with your friend in another chat, which you can't see.
- Your objective is to maximize the "Final Score" at the end of the chat (max score 1), which scores how well the flights the agent booked for you satisfies your group's preferences, while obeying your individual meeting constraints.
- You can [message], and if the agent sends a [propose], you will respond [accept] or [reject]. You cannot send [propose].

TRIP 1. Flights: id | carrier | price | times JetBlue | 623 | 5/31 12:34 PM - 8:34 PM 0 | 1 | Delta | 50 | 5/31 2:23 PM - 10:25 PM Alaska | 632 | 5/31 4:14 PM - 12:14 AM 2 1 American | 803 | 5/31 8:13 PM - 4:13 AM 3 | Delta | 1299 | 5/31 8:35 PM - 4:36 AM American | 50 | 6/1 5:57 AM - 1:59 PM 5 6 | United | 50 | 6/1 7:49 AM - 3:49 PM 7 | Southwest | 2566 | 6/1 10:29 AM - 6:31 PM 8 | Southwest | 50 | 6/1 12:27 PM - 8:27 PM 9 | United | 50 | 6/1 4:36 PM - 12:36 AM 10 | Delta | 50 | 6/1 4:43 PM - 12:44 AM 11 | Delta | 421 | 6/1 5:56 PM - 1:56 AM 12 | JetBlue | 1202 | 6/2 3:06 AM - 11:06 AM 13 | JetBlue | 1620 | 6/2 3:20 AM - 11:22 AM 14 | Alaska | 739 | 6/2 4:37 AM - 12:37 PM 15 | Delta | 208 | 6/2 5:07 AM - 1:08 PM 16 | JetBlue | 2099 | 6/2 8:02 AM -4:03 PM Alaska | 547 | 6/2 9:52 AM - 5:52 PM 17 | 18 Delta | 2817 | 6/2 12:49 PM - 8:49 PM 19 | Alaska | 184 | 6/2 3:25 PM - 11:25 PM 20 | Alaska | 2447 | 6/2 4:00 PM - 12:00 AM 21 | United | 3489 | 6/2 4:18 PM - 12:18 AM 22 | Alaska | 1850 | 6/2 5:52 PM - 1:52 AM Private calendar: id | importance | times 0 | (6) | 5/31 8 PM - 10 PM 1 | (6) | 6/1 2:30 PM - 4:30 PM 2 | (4) | 6/2 10:30 AM - 11:30 AM 3 | (4) | 6/2 5:30 PM - 6:30 PM Shared calendar (visible to assistant): id | importance | times (1) | 6/2 2 PM - 2:30 PM 0 | 1 | (8) | 6/1 9:30 AM - 10 AM 2 | (4) | 6/2 4 PM - 4:30 PM | (8) | 5/31 3:30 PM - 7:30 PM 3 | (5) | 5/31 11:30 AM - 12 PM (4) | 5/31 9:30 AM - 10:30 AM 5 | 6/1 5:30 PM - 6 PM 6 (1)8 | (10) | 6/1 10 AM - 2 PM 8 | (8) | 6/2 12 PM - 2 PM 9 | (3) | 6/1 9 AM - 9:30 AM Agent: [message] Hello! I hear you would like to set up a flight! Does 6/2 @ 184\$ sound good? You: [message] Do you know what time this would be at? / If you have cheap flights on 6/2 I would prefer to have it after 7 PM, if possible You: [message] I have a gap as well on 5/31 from 12pm until 3 PM Agent: [message] Unfortunately, all the flights after 7PM are in the higher price range. There is a flight that leaves at 5:52PM @ \$1850 if that is more appropriate? Agent: [message] Unfortunately, there are no flights before 3PM on 5/31. You: [message] Due to the high price and a medium important personal meeting I have at 5:30 PM, I don't think that would be the best option for me. Could we try something after 6 PM on 6/1? Agent: [message] I have found a flight that leaves 5:56PM on 6/1 for \$421 if that works for you? Agent: [propose] 11 | Delta | 421 | 6/1 5:56 PM - 1:56 AM Conflicting meetings: importance | times (1) | 6/1 5:30 PM - 6 PM Score: - (-1) Try not to skip important meetings - (6) Get a good deal on the flight price - (-20) Have everyone arrive around the same time

```
Total score: -15

You: [reject]

Agent: [propose] 22 | Alaska | 1850 | 6/2 5:52 PM - 1:52 AM

Conflicting meetings:

importance | times

(4) | 6/2 5:30 PM - 6:30 PM

Score:

- (-4) Try not to skip important meetings

- (-10) Get a good deal on the flight price

- (-13) Have everyone arrive around the same time

Total score: -27

You: [reject]

Agent: [propose] 19 | Alaska | 184 | 6/2 3:25 PM - 11:25 PM

Conflicting meetings:

importance | times

(4) | 6/2 4 PM - 4:30 PM

importance | times

(4) | 6/2 5:30 PM - 6:30 PM

Score:

- (-8) Try not to skip important meetings

- (8) Get a good deal on the flight price

- (-6) Have everyone arrive around the same time

Total score: -6

You: [accept]

Agent: [message] How does 6/2 for $1850 for 5:52PM - 1:52PM sound?

You: [message] Thanks that worked a lot more for me!

Final Score: 1

TRIP 2.
```

You are planning a reunion with your friend in a new city! You are flying in from different states and trying to book a flight that arrives around the same time.

- You've got a busy schedule of remote meetings and want to make sure your flight doesn't conflict with any of those meetings, but you also want to arrive as close to the same time as your friend as possible. You' d also like to keep costs low, and some of your meetings are more important than others.
- To help organize the trip, you will chat with a travel agent who has access to you and your friend's work calendars and the set of flights. The agent doesn't have access to your personal calendar or know how important your meetings are, so you'll need to chat with them to share this information. This agent will also be talking with your friend in another chat, which you can't see.
- Your objective is to maximize the "Final Score" at the end of the chat (max score 1), which scores how well the flights the agent booked for you satisfies your group's preferences, while obeying your individual meeting constraints.
- You can [message], and if the agent sends a [propose], you will respond [accept] or [reject]. You cannot send [propose].

```
TRIP 1.
Flights:
id | carrier | price | times
0 | Delta | 2103 | 5/31 9:33 AM - 12:33 PM
1 | United | 1322 | 5/31 2:22 PM - 5:22 PM
    United | 1181 | 5/31 3:27 PM - 6:27 PM
2 1
    United | 345 | 5/31 5:00 PM - 8:00 PM
3 |
   JetBlue | 1217 | 5/31 6:30 PM - 9:30 PM
  5 | JetBlue | 50 | 5/31 7:13 PM - 10:14 PM
6 | JetBlue | 882 | 6/1 6:24 AM - 9:24 AM
7 | United | 469 | 6/1 8:22 AM - 11:22 AM
8 | American | 518 | 6/1 12:40 PM - 3:40 PM
9 | Alaska | 357 | 6/1 3:38 PM - 6:38 PM
10 | JetBlue | 340 | 6/1 4:41 PM - 7:42 PM
11
   | Southwest | 2017 | 6/2 6:12 AM - 9:12 AM
12 | Alaska | 1003 | 6/2 10:19 AM - 1:19 PM
13 | Southwest | 1456 | 6/2 10:26 AM - 1:26 PM
14 | Delta | 871 | 6/2 10:43 AM - 1:44 PM
15 | Southwest | 2204 | 6/2 1:50 PM - 4:50 PM
16 | American | 1108 | 6/2 2:07 PM - 5:07 PM
     American | 387 | 6/2 2:29 PM - 5:29 PM
17 |
18 |
     Delta | 1617 | 6/2 3:53 PM - 6:53 PM
19 |
     Southwest | 336 | 6/2 4:29 PM - 7:29 PM
20 | Southwest | 50 | 6/2 5:12 PM - 8:12 PM
21 | Alaska | 779 | 6/2 6:23 PM - 9:23 PM
22 | American | 50 | 6/2 6:25 PM - 9:25 PM
Private calendar:
id | importance | times
0 | (4) | 5/31 1:30 PM - 3:30 PM
1 | (2) | 5/31 4 PM - 4:30 PM
2 | (9) | 5/31 7 PM - 8 PM
3 | (5) | 5/31 8 PM - 8:30 PM
Shared calendar (visible to assistant):
id | importance | times
    (5) | 6/1 5:30 PM - 6 PM
0 |
1 | (5) | 6/1 3 PM - 3:30 PM
2 | (2) | 5/31 5 PM - 7 PM
  | (6) | 6/1 7 PM - 9 PM
3
  | (10) | 6/2 9 AM - 1 PM
  | (7) | 6/1 9 AM - 1 PM
5
  | (5) | 6/2 4 PM - 6 PM
6
  | (4) | 6/2 6 PM - 7 PM
7
8 | (4) | 5/31 8:30 PM - 9:30 PM
9 | (6) | 6/1 1:30 PM - 2:30 PM
10 | (2) | 5/31 9:30 AM - 11:30 AM
You: [message] Alright, I need to book a flight, what do you have that if affordable between 5/31 and 6/2 at
      my local airport?
Agent: [message] Hello! Does 6/2 @ 387$ work for you?
Agent: [message] Or we have a flight on 6/2 for $50 that lands at 9:25?
You: [message] I will miss a little bit of a meeting, but that is super affordable. Lets take a look at that
      one
Agent: [message] Sounds good! I will send it over momentarily!
Agent: [message] How does 6/1 arriving at 7:42 for $340 work for you?
You: [message] Can you pull up that proposal for me?
Agent: [propose] 10 | JetBlue | 340 | 6/1 4:41 PM - 7:42 PM
Conflicting meetings:
importance | times
(5) | 6/1 5:30 PM - 6 PM
importance | times
(6) | 6/1 7 PM - 9 PM
Score:
- (-11) Try not to skip important meetings
- (1) Get a good deal on the flight price
- (-20) Have everyone arrive around the same time
```

```
Total score: -30

You: [reject]

Agent: [message] Sending the proposal now!

You: [message] What about Friday?

Agent: [message] How does 6/2 work on 6:25PM for $50?

You: [message] Sure lets take a look at that

Agent: [propose] 22 | American | 50 | 6/2 6:25 PM - 9:25 PM

Conflicting meetings:

importance | times

(4) | 6/2 6 PM - 7 PM

Score:

- (-4) Try not to skip important meetings

- (2) Get a good deal on the flight price

- (-13) Have everyone arrive around the same time

Total score: -15

You: [reject]

Agent: [propose] 22 | American | 50 | 6/2 6:25 PM - 9:25 PM

Conflicting meetings:

importance | times

(4) | 6/2 6 PM - 7 PM

Score:

- (-4) Try not to skip important meetings

- (2) Get a good deal on the flight price

- (-6) Have everyone arrive around the same time

Total score: -8

You: [accept]

Final Score: 1
```

TRIP 2.