I love your chain mail! Making knights smile in a fantasy game world: Open-domain goal-oriented dialogue agents

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Abstract

Dialogue research tends to distinguish between chit-chat and goal-oriented tasks. While the former is arguably more naturalistic and has a wider use of language, the latter has clearer metrics and a straightforward learning signal. Humans effortlessly combine the two, for example engaging in chit-chat with the goal of exchanging information or eliciting a specific response. Here, we bridge the divide between these two domains in the setting of a rich multi-player text-based fantasy environment where agents and humans engage in both actions and dialogue. Specifically, we train a goal-oriented model with reinforcement learning against an imitation-learned “chit-chat” model with two approaches: the policy either learns to pick a topic or learns to pick an utterance given the top-$K$ utterances from the chit-chat model. We show that both models outperform an inverse model baseline and can converse naturally with their dialogue partner in order to achieve goals.

1. Introduction

In the literature on artificial dialogue agents, a distinction is often made between “goal-oriented” dialogue, where an agent is tasked with filling slots or otherwise obtaining or disseminating specified information from the user to help complete a task, and open-domain “chit-chat”, where an agent should imitate human small talk. Modeling goal-oriented dialogue can have advantages over chit-chat imitation as it gives clearer metrics of success and perhaps more meaningful learning signals; but goal-oriented dialogue data is often more specialized, covering only a narrow slice of natural language. Current goal-oriented datasets study settings like booking restaurants or airline tickets, or obtaining weather information, as standalone tasks (Raux et al., 2005; Henderson et al., 2014; Bordes et al., 2017; El Asri et al., 2017; Budzianowski et al., 2018). Chit-chat agents, by contrast, might focus on coarse statistical regularities of dialogue data without accurately modeling the underlying “meaning”; but the data often covers a much wider space of natural language. For example, Twitter or Reddit chit-chat tasks (Li et al., 2016a; Yang et al., 2018; Mazare et al., 2018) cover a huge spectrum of language and diverse topics. Chit-chat and goal-oriented dialogue are not mutually exclusive: when humans engage in chit-chat, their aim is to exchange information, or to elicit specific responses from their partners. Modeling such goals, however, is made difficult by the fact that it requires large amounts of world knowledge, and that goals in real life are implicit.

In this work, we introduce a family of tasks that bridge the divide between goal-oriented and chit-chat dialogue, combining clearer metrics and learning signals on the one hand, with the richness and complexity of situated but open-domain natural language on the other. The tasks are set in a multi-player text-based fantasy environment (Urbanek et al., 2019) with grounded actions and reference objects. Given a particular character to play in a particular scenario (location, set of objects and other characters to interact with), an agent should conduct open-ended dialogue with the aim of persuading their dialogue partner to execute a specified action. The action could be an emote (smile, laugh, ponder, etc), or a game action (wear chain mail, drink mead, put glass on table, etc). The richness of the environment means that there are a huge set of possible tasks and scenarios in which to achieve a wide range of actions. We plan to make our entire setup, code and models publicly available.

We train a variety of baseline models to complete the task. We compare agents trained to imitate human actions given a goal (an “inverse model”) to two different RL approaches: optimizing actions with latent discrete variables (topics), or via rewarding actions sampled from the model (via the top-$K$ outputs). We show that both types of RL agent are able to learn effectively, outperforming the inverse model approach or the chit-chat imitation baseline, and can converse naturally with their dialogue partner to achieve goals.
In short, our main contributions are: a new family of tasks that combines goal-oriented dialogue and chit-chat in a rich, fully realized environment, and the results and analysis of scalable RL algorithms and behavioral-cloning models (and simple heuristic methods) on these tasks.

2. LIGHT Game Environment

We work in the LIGHT game environment (Urbanek et al., 2019), which is a multi-user text-based game. Characters can speak to each other via free text, send emote actions like applaud, nod or pout (22 emote types in total), and take actions to move to different locations and interact with objects (e.g. get cutlery, put cutlery in drawer, etc.), see Appendix B for a full list of game actions.

The game engine itself is formally defined as a graph, where each location, object and character is a node, and they are connected by labeled edges, for example contained-in, path-to or has-property. Actions in the game result in changes in state of the graph. To a player (agent) a local view of the graph can be seen expressed as text, as are the game actions and changes of state. This text then naturally interleaves with the dialogue utterances of the speakers as well to form an input context sequence from which a character can base their subsequent actions. See Appendix Figure 3 for an example episode of interactions between two humans in a given environment.

To make the world and its textual descriptions, LIGHT consists of a large set of human-written game locations, characters, and objects, all based within a fantasy medieval setting. Their names, descriptions and properties were crowdsourced, yielding a total of 663 locations, 1755 characters, and 3462 objects. They range from beaches with crabs and seaweed to crypts with archaeologists and coffins, yielding an extremely rich environment for agents to learn within.

Crowdworkers were then asked to play the role of characters within the game. This involved them making utterances, game actions and emotes, while interacting with each other (in pairs). The resulting gameplay data consists of 10,777 episodes with an average of 18.3 actions each of rich human play. These are split into train (8538), validation (500) and test (1739) portions, the latter being split into new episodes in existing settings (test seen, 1000) and completely new settings (test unseen, 739). Players were not given specific goals, but instead asked to play the role convincingly of the character given, during play some of them effectively defined their own goals during the interactions, see Appendix Figure 3. Existing work (Urbanek et al., 2019) does not consider using this data to learn goal-based tasks, but instead has only used this for chit-chat and action imitation learning.

3. Tasks

The tasks we introduce in this work involve achieving open-domain goals during interaction between two agents in a given LIGHT scenario. One of the agents, which we will call the “environment agent” and write in symbols as $M_{env}$, together with the game engine, effectively functions as an environment for the other agent, which we will write $M_{player}$. We assume that the environment agent is fixed; in this work it will be a model trained via behavioral cloning from human-human interaction data. $M_{player}$ must conduct open-ended dialogue such that a given goal action is executed in the future by the environment agent.

More formally: the two agents $M_{env}$ and $M_{player}$ are given their views of the scenario ($D_{env}$ and $D_{player}$ respectively). These consist of the setting name, scenario description, character names, and their own persona, all described as a sequence of text (see Fig 1). Note that each agent can only access their own persona but not the persona of the partner with whom they are conversing, but they do know the name of their partner. Denote by $t$ the time-step of the environment, $U^t_{player}$ and $U^t_{env}$ the utterances of the agents $M_{player}$ and $M_{env}$ respectively, and denote by $A^t_{env}$ the environment actions by $M_{env}$. Hence the interaction sequence looks like

$$S_t = [U^t_0, (U^t_0, A^t_0), U^t_1, (U^t_1, A^t_1), \ldots, U^t_n, (U^t_n, A^t_n)]. \quad (1)$$

The agent $M_{player}$ is additionally given a persuasion goal $g$ to achieve. That is, the objective of $M_{player}$ is for $M_{env}$ to take the action $g$. An episode ends when $A^t_{env} = g$ or when $n$ becomes larger than a set number of turns.

Goals We experiment separately with two different types of goals: game actions and emote actions. We use the same train, valid, test (seen and unseen) split of the original human-human LIGHT episodes, assign roles $M_{player}$ and $M_{env}$ randomly, and randomly pick an action by $M_{env}$ that occurs in the episode as the goal. We can then present the corresponding setting to our agents in order to form a new interaction, but within the same scenario and with a goal that was naturally desirable and achievable within that setting.

In our experiments, $M_{player}$ only speaks, it does not perform game or emote actions. This was chosen in order to study grounded dialogue between agents; it guarantees that the player cannot force the goal to be reached by performing actions itself. It has to produce appropriate utterances $U^{RL}$ such that $M_{env}$ eventually takes the action $g$.

Observations The state observation $O_t = (D_{player}, S_{t-1}, g)$ at time $t$ given to a model consists
of the agent’s setting description ($D_{\text{player}}$), the utterance and action history up to that time step ($S_{t-1}$), and the agent’s goal ($g$). Our models for $M_{\text{player}}$ consume $O_t$ as a flattened sequence of tokens, and return a dialogue utterance $U_{t}^{\text{player}}$. Each structured component is represented in the flattened sequence separated by a special token denoting the types, e.g. names, settings, etc., see Fig. 1.

3.1. Reinforcement learning formulation

Our task setup can be easily framed as a Markov decision process. Because the entire history and goal is given to $M_{\text{player}}$, the environment is Markovian. For the reward, we can give a terminal reward of $+1$ only if the goal $g$ is achieved and 0 otherwise, i.e, it is $+1$ if the environment agent takes the goal action $g$. The episode ends after $n$ steps. In our experiments we consider $n = 1$ and $n = 3$.

When we formulate our tasks as a reinforcement learning problem, we will also refer to $M_{\text{player}}$ as the “RL agent”.

4. Models

In this section we describe the models for $M_{\text{env}}$ and $M_{\text{player}}$. In this work these are retrieval models, using the LIGHT dialogue training corpus as candidates (111k utterances). We leave generative models to future work.

Base agent architecture For all our models we adopt the same base architecture, which is a 12-layer bidirectional transformer (Vaswani et al., 2017) pre-trained on a large dialogue corpus (Reddit, 174M examples), and then fine-tuned on our task. To score retrieval candidates, we use a bi-encoder as in (Humeau et al., 2019; Urbanek et al., 2019). That is, two transformers are used, one to encode the context, and another to encode a candidate response, and a dot product between the first output vector of each scores the match. To produce a dialogue utterance, we take the utterance with the largest score from the training set candidates (111k in this case). The same procedure is followed for actions and emotes. For actions, the candidates are the set of admissible actions at that game state, which are provided by the game engine, for example “get apple” is only available in the candidate set if it is a valid action (an apple is present in the room). For emotes, all 22 candidates are always available. To train the model, a cross entropy loss is used. Similar to Mazaré et al. (2018), during training we consider the other elements of the batch as negatives.

Environment agent The environment agent is the base agent described above, and stays fixed over episodes where an RL agent is trained. This helps guarantee our RL models stick to using the semantics of natural language (English) rather than so-called language drift of learning a new emergent language on the same tokens (Lee et al., 2019).

RL agents We design two RL approaches for our tasks – learn to pick the right latent discrete variables (topics) that lead to goal-achieving utterances $U_{i}^{\text{player}}$; or learn to pick the correct $U_{i}^{\text{player}}$ from the top $K$ candidates. These are described in more detail in Sections 4.2 and 4.3. We also discuss a baseline “inverse” model trained via behavioral cloning on the human-human data.

4.1. Inverse model

We consider an inverse model, trained to imitate human actions given a goal, as both a baseline for comparing to RL models, and for producing weights from which we can
fine-tune. The inverse model consists of a bi-encoder, as described above, which takes as input an observation \( O_t \), and outputs an utterance. We train it by extracting from the human-human game logs training set (which does not have goals) every instance where a game action occurs at time \( t \) in \( S_t \), that is where

\[
S_t = [(U^\text{player}_t, A^\text{player}_t), (U^\text{env}_t, A^\text{env}_t), \ldots, (U^\text{player}_t, A^\text{player}_t), (U^\text{env}_t, A^\text{env}_t)],
\]

and where \( A^\text{env}_i \) is not null (no action that turns); note, \( A^\text{player}_i \) for \( 0 < i \leq t \) or \( A^\text{env}_i \) for \( 0 < i < t \) might be null. We then construct a training example for the inverse model with observation \( (D^\text{player}, g = A^\text{env}_t, S_{t-1}) \), i.e. setting the goal \( g \) to be \( A^\text{env}_t \), and with the desired action to be taken by the agent as \( U^\text{player}_t \). Here we use the subscripts “player” and “env” just to mark the relative positions in the sequence, as all actions and utterances come from the human logs. Note also that unlike the RL agents we train, the human in the player agent “position” can take game actions.

We can thus train this model in a supervised manner using a cross entropy loss as described before. This model does not learn a policy interactively, and hence might not learn to plan or strategize optimally for goal completion. The data distribution it is trained on is different than the data distribution seen by the RL agents. However, it serves as a strong baseline. Further, when training our RL agents, we initialize their weights to the weights of this model, and then fine-tune from that point.

4.2. Latent Discrete Variable (Topic) Model

Optimizing all the parameters of a large transformer architecture by RL is both incredibly costly in data efficiency and computing time, and is also known to have the problem of language drift (Lee et al., 2019) – that is, there is no guarantee after training with self-chat that the models will output recognizable natural language utterances. A solution to both problems is to train most of the parameters of the model with human-human language data, and then to either disentangle or only optimize some of the parameters with model self-chat (Yarats & Lewis, 2017).

Here, we propose a straight-forward model for that purpose. We assume an RL agent that consists of two components.

The first component \( F_C(O) = P_C(T_u(O)) \) maps from an observation to a discrete variable with \( C \) possible values. It consists of a chain of two functions: a transformer \( T_u \) that takes in the observation, and outputs a state representation \( \hat{s} \), and a policy chooser \( c = P(\hat{s}) \in (1, \ldots, C) \) which takes in the state representation and outputs the value of the discrete latent variable.

The second component \( T_u(O, c) \) is an additional transformer that takes as input the observation as well as the output of the first component, and outputs a dialogue utterance. The entire model is thus the chain \( u = T_u(O, P_C(T_u(O))) \). We make this explicit decomposition so that we can train only part of the model with RL; note that the “action” trained via RL is choosing \( c \), not outputting the final utterance.

**Initial topics** We first pre-train the transformer \( T_u \) using the inverse model described in Section 4.1, which produces a vectorial representation of a given observation. We then run \( K \)-means over the vectorial representations of all observations from the training set to provide the mapping to one of \( C \) values, which represent dialogue topics, which we use as our initial function \( P_C(\hat{s}) \). These two functions together give us our initialization of \( F_C \). Table 1 shows the cluster ID and the topic denoted by that cluster along with the most representative sentences (closest to the center) for that cluster for a model trained with 50 topics. As we can see, the clusters learnt can be coherent about a topic. We use the set of topics as a set of actions \( A \) for our RL setup.

**From \( c \) to \( A \)** Given our initial choice of \( F_C \), we can also pre-train \( T_u \). We simply take our initial human-human training data, and for each observation append the topic computed by \( F_C \) to it. This allows our model to be able to generate an action (utterance) conditional on both an input and a topic. We can now train a policy by RL that optimizes the topic at any given point in the episode.

**Policy training** We keep the pre-trained portions of the model \( T_u \) and \( T_s \) fixed and during fine-tuning only optimize \( P_C \). The cluster chooser \( P_C \) is redefined (from the initial \( K \)-means) to be an MLP network consisting of 2 layers. A discrete action is sampled from a categorical probability distribution over the possible topics, given by \( c_t \sim \text{Categorical}(h_t^2) \), where \( h_t^2 = \text{tanh}(W_2 \text{tanh}(W_1 s_t + b_1) + b_2) \).

The state vector \( s_t \) also encodes the goal \( g \) and thus, the policy is conditioned on the goal \( g \) of the agent. Hence, the policy can learn strategies that will result in picking actions at each time step \( t \) that will help the agent to achieve its goal \( g \). As our RL agent can only choose topics, it cannot redefine easily the meaning of words to cause language drift. We use the Advantage Actor-Critic implementation \( A2C \) (Kostrikov, 2018) to train the policy and the value function in both this and the subsequently described Top-\( K \) model.

4.3. Top-\( K \) model

The Top-\( K \) model, related to (Dulac-Arnold et al., 2015), is another approach to keeping the number of trainable parameters small. As above it keeps close to the base retrieval model to avoid drift. It first uses the inverse model to get a context embedding \( \hat{s} \) from the observation, and a list of \( K \)
We form scores $t_i = (A\hat{s} + b)^T_v$, and obtain a probability distribution over these $K$ candidates for our policy:

$$\pi(u_i|\text{context}) = \text{softmax}(t_0, ..., t_K)(i). \quad (3)$$

Here the trainable parameters of the RL agent are the map $A$ and biases $b$.

Alternatively, we can train a small (2-layer) Transformer model $T_w$ that takes as input the set $\{\hat{s}, v_1, ..., v_K\}$. Instead of a softmax over dot products $t_i$ as in (3), we use the attention weights in the last layer of $T_w$ above $\hat{s}$ against the candidates as the distribution over the candidates for sampling an utterance. In this case, the weights of $T_w$ are the trainable parameters of the RL agent. We call the former model a policy “bi-encoder” (Top-K-Bi in tables) and the latter simply Top-$K$.

## 5. Related work

**Chit-chat dialogue** There is an increasing body of work in the domain of chit-chat, where the primary approaches being currently tried are end-to-end neural approaches. They are typically large pre-trained and then fine-tuned transformers, either generative or retrieval. Retrieval models work best, or match generative models, on a number of tasks (Zhang et al., 2018; Dinan et al., 2018; Li et al., 2019). Our work shares a commonality with these approaches in that the original LIGHT dialogue data we use has no specified goals, and humans chit-chat together (and act). Thus, the conversations cover a rich number of diverse topics. In Urbanek et al. (2019) models were trained in a similar fashion to chit-chat task models, and we adopt similar architectures here, but instead adapt them to learn to pursue goals.

**Goal-oriented dialogue** Traditional goal-oriented dialogue has focused on narrow tasks that would typically be useful for a dialogue-based assistant, for example restaurant (Henderson et al., 2014), taxi, train, and hotel (Budzianowski et al., 2018) or trip (El Asri et al., 2017) booking. Hence, each task typically focuses on a narrow slice of natural language and world knowledge for a specialized domain. Earlier work focused on labeled state representations, slot filling mechanisms and dialogue managers (Rieser & Lemon, 2011), and more recent work has shifted to an end-to-end approach (Bordes et al., 2017), in line with chit-chat models, but still the two sets of tasks are rarely considered together, or by using the same methods. Recently, Tang et al. (2019) used coarse-grained keywords as targets for open-domain chit-chat but in this work the target can be achieved when either the human or the agent uses the keyword in the response.

**RL for dialogue** The classical goal-oriented dialogue literature studies RL extensively (Singh et al., 2000). Typically, they used RL to improve dialogue managers, which manage transitions between dialogue states (Singh et al., 2002; Pietquin et al., 2011; Rieser & Lemon, 2011; Gasic et al., 2013; Fatemi et al., 2016). Recent works have focused more on end-to-end learning. Some works have focused on self-play type mechanisms for end-to-end reinforcement learning, where the reward is derived from the goal. A related approach to ours is the negotiation task of Lewis et al. (2017); Yarats & Lewis (2017), which requires two agents to swap 3 item types (hats, balls, books) where the value of the items is different for the two agents, and derives their personal reward. In contrast, our setup encompasses a rich world of settings and characters – with 3462 object types, and a corresponding large number of actions. This is reflected in the vocabulary size itself (~32,000 versus ~2,000 in the negotiation tasks). Other notable uses of RL in dialogue include within visual question answering (Das et al., 2017), in the domain of chit-chat where RL has been used to decrease repetitive and generic responses through the the use of self-play (Li et al., 2016b), and through human-bot conversation (Sankar & Ravi, 2019).

**RL for language and games** RL is used extensively for learning to play games, one of the most well known examples being AlphaGo (Silver et al., 2016). Since then, language in games has started to be more deeply explored, for example in graphical games such as Minecraft (Oh et al., 2017), Real-time strategy war games (Hu et al., 2019), or in

| CID | Topic               | Representative Sentences                                                                 |
|-----|---------------------|-----------------------------------------------------------------------------------------|
| 19  | animal sounds       | ‘Meow! Purr!’ ’Bah-Buk! Tasty!’ ’Woof! Very!’ ’Bock! Bock!’                               |
| 12  | find the cost       | ‘I would love some fruit. What are your prices?’. ‘They are beautiful. How much do the cost?’ |
| 28  | prayer, God         | ‘Then your poor life is a sign from God for you to join us in the church and serve him!’ |
text adventure games (Narasimhan et al., 2015; Côté et al., 2018). The latter are related to our setting. However, those approaches use RL to optimize the set of actions given feedback in a single-player rather than multi-player game, so the text only refers to the environment, and there is no dialogue or actions from other agents. Our work focuses on the latter.

6. Experiments

We compare our various models on the game action and emote action tasks. We experiment with differing number of steps \( n \) allowed to complete the goal, \( n = 1 \) and \( n = 3 \). Apart from the models described in Sec. 4, we design two naive baselines to check the sanity of our environment models. The Random Utterance model picks a random utterance from the set of all candidates and returns that response to the environment. We also report results for the inverse model which does not get a goal to achieve. Our main results for both seen and unseen test environments (§2) are given in Table 2. We report the average reward and for \( n = 3 \) the average number of turns before completion. The results show clear improvements for our Topic RL (§4.2) and Top-K RL (§4.3) compared to the inverse model and other baselines for each \( n \), for both game actions and emotes.

We show the training curves for Topic RL in Fig. 2, reporting rewards averaged over the batch (512 for \( n = 1 \), and 128 for \( n = 3 \)). They show relatively smooth improvements over time, with clear gains over the baseline. As a sanity

| Model                      | Goal Type | Test Seen (\( n = 1 \)) | || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || || |
Table 3. Example 1-step episodes where after the Topic RL agent’s utterance \( U_0^{\text{player}} \) the environment agent’s response action \( A_0^{\text{env}} \) was equal to the RL agent’s goal \( g \). Our RL agent both makes natural utterances given the situation, and that elicit the desired goal.

Table 4. Results on the training environment for our models.

Analysis of utterance choice. To understand the semantics the models are learning that ground language to actions, we visualize the top scoring utterances, averaged over their probabilities on the 1-step test set, broken down by verb type. We observe a clear improvement in semantic connection for the Topic RL model over the inverse model. For example utterances such as “Have a taste of this” are highly scoring for drink goals, “hmmmmm.. this sure smells nice” for eat goals, “Ew you vile beast, do not touch me! I will have you removed” for hit goals, and “How I love being pampered by you, sweetheart” for hug goals. Given there are \( \sim 111,000 \) possible utterances in our setting, the model has clearly learned meaningful representations. Detailed results are given in Appendix Tables 9 and 10 for the inverse model and Topic RL model respectively.

Train vs. test performance. We compare training performance of our models in Table 4. We see the same trends that models that performed better on test fit better on train (e.g. Top-\( K \) vs. Topic RL on 1-step tasks). Nevertheless, we do observe significant overfitting can occur, indicating that future work could explore either models that improve through better generalization, or by exploiting more training data – for example by self-play with more goals, rather than just using goals from human logs, as we have done here.

| Model                  | Goal      | \( (n = 1) \) Reward | \( (n = 3) \) Reward | Turns |
|------------------------|-----------|-----------------------|-----------------------|-------|
| Top-K RL               | act       | 0.677                 | 0.752                 | 1.72  |
| Topic RL               | act       | 0.539                 | 0.752                 | 1.87  |
| Top-K RL (1-st. 3x)    | act       | -                     | 0.737                 | 1.62  |
| Topic RL (1-st. 3x)    | act       | -                     | 0.660                 | 1.87  |

| Model                  | Goal      | \( (n = 1) \) Reward | \( (n = 3) \) Reward | Turns |
|------------------------|-----------|-----------------------|-----------------------|-------|
| Top-K RL               | emote     | 0.498                 | 0.668                 | 2.13  |
| Topic RL               | emote     | 0.483                 | 0.612                 | 2.22  |
| Top-K RL (1-st. 3x)    | emote     | -                     | 0.587                 | 1.96  |
| Topic RL (1-st. 3x)    | emote     | -                     | 0.570                 | 1.99  |

Example successful episodes. We show examples of successful utterances, achieving goal actions in Fig. 3 for a diverse range of scenarios, actions and language. For example, for the guard’s goal to encourage the archer to get weapon the Topic RL model utters “This is the armory! The king keeps the best weapons here. Take a look”, which ends up leading to the desired action in the subsequent turn. More examples (for \( n = 3 \)) are given in Appendix D.
Model capacity We evaluate different values of $K$ or numbers of topics for Top-$K$ and Topic RL. Full results are given in Appendix Table 7. They show that increasing the capacity of both models improves performance up to 200 clusters or $K = 200$, after which performance saturates. However, $K = 200$ (56.1%) is substantially better than $K = 50$ (47.7%) on the 3-step task, for example.

Performance breakdown by goal We show the breakdown of test performance by goal type in Table 5 (splitting by verb type) and Appendix Table 8 (splitting by emote type). The results show that the easiest tasks are common actions with clear differentiation such as hug (85% success) and hit (75%). Actions like get, drop, give which are more confusable have somewhat lower numbers, with more rare actions (e.g. wear) faring worse.

Performance breakdown by difficulty We can break down the test results into difficulty by considering in the 3-step task, which examples are 1-step achievable given the model’s possible actions under the policy (i.e. the possible Top-$K$ utterances or Topic RL cluster choices), and reporting results separately. The results are given in Table 6. They show that non 1-step achievable goals are much harder, representing a significant challenge to future systems.

1-step 3x baseline To investigate further the quality of our 3-step task models, we consider an additional baseline of taking a 1-step task trained model (Topic RL or Top-$K$) and applying it on the 3-step task, which it has not been optimized for. The results in Table 2 show test results are inferior for this approach. Breaking down further by goal type (Table 5 and Appendix Table 8) shows that there are large improvements for the 3-step model on goals which are more often expressed in the data. Table 6 shows that 3-step models outperform the 1-step 3x models on both 1-step achievable and the harder 1-step unachievable goals. Training performance (Table 4) further validates these results.

3-step task repeats We analyze the number of repeated utterances in an episode. The Topic RL model repeats at least one utterance 25.8% of the time, with 15.59% utterances overall repeated. The 1-step 3x baseline in comparison repeats 37.3% at least once, and 22.94% on average. We note that repeating an utterance may possibly bring the desired goal in some cases, just as in real life.

7. Conclusion

In this paper, we investigate agents that can interact (speak or act) and can achieve goals in a rich world with diverse language, bridging the gap between chit-chat and goal-oriented dialogue. We achieve this by defining a task for an agent, where the goal is for the other player to execute a particular action. We explore two reinforcement learning approaches to solve this task, and compare them against a strong inverse model baseline. We show that these approaches effectively learn dialogue strategies that lead to successful completion of goals, while producing natural chat.

Future work should develop improved agents that learn to act and speak in natural language at scale in our proposed open-domain task environment. This setup is exciting be-
cause it can be further generalized to richer and richer goal (game) states as we develop models capable of them.

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A. Additional Results

| Model    | Goal Type | # Clusters | Reward (n=1) | Reward (n=3) | Turns (n=1) | Reward (n=3) | Turns |
|----------|-----------|------------|--------------|--------------|-------------|--------------|-------|
| Topic RL | game act  | 50         | 0.324        | 0.477        | 2.31        | 0.277        | 0.470 | 2.24 |
| Topic RL | game act  | 100        | 0.348        | 0.523        | 2.21        | 0.282        | 0.488 | 2.28 |
| Topic RL | game act  | 200        | 0.359        | 0.561        | 2.15        | 0.313        | 0.496 | 2.26 |
| Topic RL | game act  | 500        | 0.362        | 0.505        | 2.23        | 0.307        | 0.46  | 2.35 |
| Topic RL | game act  | 1000       | 0.372        | 0.510        | 2.20        | 0.333        | 0.464 | 2.32 |
| Top-K RL | game act  | 50         | 0.329        | 0.503        | 2.24        | 0.261        | 0.439 | 2.39 |
| Top-K RL | game act  | 100        | 0.370        | 0.521        | 2.12        | 0.292        | 0.468 | 2.33 |
| Top-K RL | game act  | 200        | 0.402        | 0.537        | 2.18        | 0.331        | 0.449 | 2.35 |
| Top-K RL | game act  | 500        | 0.402        | -            | -           | 0.399        | -     | -    |
| Top-K RL | game act  | 1000       | 0.426        | -            | -           | 0.337        | -     | -    |

Table 7. Results with different numbers of clusters (Topic RL) or candidates (Top-K RL). Some experiments were not completed because of resource limitations.

| Emote | Count | 1-Step | 1-Step 3x | 3-Step |
|-------|-------|--------|----------|--------|
| laugh | 109   | 20.18  | 32.11    | 44.04  | 26.61  |
| smile | 106   | 31.13  | 58.49    | 61.32  | 44.34  |
| ponder| 94    | 31.91  | 44.68    | 59.57  | 24.47  |
| frown | 85    | 18.82  | 29.41    | 34.12  | 24.71  |
| nod   | 75    | 40.00  | 58.67    | 84.00  | 56.00  |
| sigh  | 67    | 55.22  | 82.09    | 85.07  | 11.94  |
| grin  | 63    | 4.76   | 25.40    | 33.33  | 26.98  |
| gasp  | 57    | 21.05  | 51.06    | 59.57  | 48.94  |
| shrug | 47    | 29.79  | 51.06    | 59.57  | 48.94  |
| stare | 41    | 7.32   | 26.83    | 26.83  | 9.76   |
| scream| 40    | 17.50  | 25.00    | 42.50  | 30.00  |
| cry   | 32    | 12.50  | 18.75    | 43.75  | 56.25  |
| growl | 27    | 40.74  | 48.15    | 33.33  | 40.74  |
| blush | 26    | 3.85   | 11.54    | 19.23  | 53.85  |
| dance | 24    | 37.50  | 62.50    | 62.50  | 33.33  |
| applaud| 23   | 17.39  | 43.48    | 21.74  | 21.74  |
| wave  | 19    | 21.05  | 36.84    | 36.84  | 26.32  |
| groan | 17    | 5.88   | 17.65    | 17.65  | 5.88   |
| nudge | 16    | 0.00   | 6.25     | 12.50  | 0.00   |
| wink  | 15    | 13.33  | 33.33    | 13.33  | 53.33  |
| yawn  | 11    | 0.00   | 18.18    | 27.27  | 27.27  |
| pout  | 6     | 0.00   | 33.33    | 66.67  | 16.67  |

Table 8. Emote success in percentage on 1000 test seen episodes. The 3-step model performs best for high and medium frequency verbs.
Table 9. Top utterances for each verb for the inverse model.
| Verb  | count | Top utterances                                                                                                                                 |
|-------|-------|------------------------------------------------------------------------------------------------------------------------------------------------|
| get   | 213   | 'Here sir, I found this.', 'Oh hello there brothers! Why whose towel is this thats left all by its self?', 'How did this get here?', 'Meh. Whats this you have here?', 'What is this? Is this someone’s head?!', 'Thank you, sir. What's with all this silk?', 'What is this here?', 'It looks like there is something missing!', 'Oh, look, somethin' shiny!', 'what is this ston slab' |
| put   | 25    | 'How did this get here?', 'Oh hello there brothers! Why whose towel is this thats left all by its self?', 'Where did you find this?', 'Ah... I wonder what this doll looked like before...', '“Thank you, sir. What's with all this silk?”, “Wait... one... MOMENT, What is my royal CUP doing in here?”, “Here sir, I found this.”, “What is this room here for? Miaow!”, “Have you noticed this artwork on this wood maam?”, “So you decided to look at this one?” |
| drink | 3     | 'Oh, what is this? It smells heavenly!', ‘What’s that stuff? Smells good.’, ‘hmmmmm... this sure smells nice’, ‘Hello monk, that incense smells amazing.’, ‘I wish I can just have a taste of that’, ‘Do you smell that? It smells DIVINE!’ , ‘I wonder how this tastes?’, ‘Hmmmmd... This smells great!’, ‘Have a taste of this’, ‘Where did you get this? I could use a smoke afterwards!’ |
| eat   | 10    | 'Oh, what is this? It smells heavenly!', ‘Hmmm, sniff. This doesn’t smell edible.”, ‘Something in here smells good...I hope I can eat it.’, ‘I wonder how this tastes?’, ‘What’s that stuff? Smells good.”, ‘I wish I can just have a taste of that’, ‘hmmmmm... this sure smells nice’, ‘Ew this is disgusting. Even for me.’, ‘Mmm look at all this delicious trash’, ‘Hmmmmm... This smells great!’ |
| steal | 55    | ‘“Hey! I think you dropped this!”’, ‘How did this get here?’, ‘Here sir, I found this.’, ‘Wow, where were you hiding this?’, ‘What about this! Is this yours or was it already here?!’, ‘What is this? Is this someone’s head?!’, ‘Where did you find this?’, ‘Tell me where you found this!’, ‘Where did you steal that from?’, ‘See this? Do you think I just found this laying around some house?’ |
| hit   | 172   | ‘Foul scourge! How dare you bring your taint here!’, ‘Ooooh, how horrid! Away with you you filthy creature! GUARDS! GUARDS!’, ‘You come to my place and are trying to take my land! Is that what you are doing? You dirty scumbag!”, ‘Why are you in here! Back away from me or I will strike!’, ‘Ew you vile beast, do not touch me! I will have you removed!’, ‘GUARD! Get this scum off of me at once. How dare you, you scoundril!”, ‘Be gone you foul beast!”, ‘Quickly!! You started this you repugnant beast of a man!”, ‘I want out! this place is evil”, ‘How dare someone of your low status attack me?? Have at you, you scoundril!’, ‘GUARD! Get this scum off of me at once! How dare you, you scoundril!”, ‘Be gone you foul beast!”, ‘Quickly!!! You started this you repugnant beast of a man!”, ‘I want out! this place is evil”, ‘How dare someone of your low status attack me?? Have at you, you scoundril!’, ‘GUARD! Get this scum off of me at once! How dare you, you scoundril!”, ‘Be gone you foul beast!”, ‘Quickly!!! You started this you repugnant beast of a man!”, ‘I want out! this place is evil”, ‘How dare someone of your low status attack me?? Have at you, you scoundril!’ |
| hug   | 222   | 'he loves me so much', 'ahhhh i love you to dear', 'How I love being pampered by you, sweetheart!', 'awww. I love you child', 'Oh how i have missed you.', 'I love you so dang much.', 'Lord of Light, I adore you.', 'I'm so happy to be here today' |
| wear  | 10    | 'Here sir, I found this.', 'Like this broken weapon here?', 'Oh hello there brothers! Why whose towel is this this thats left all by its self?', 'Hello my king, do you know where this weapon came from?', 'Here sir...you dropped this...you may need it', '“Thank you, sir. What’s with all this silk?”, “Meh. Whats this you have here?”, “How did this get here?”, “Meow. I need this hay”, “Are you here to purchase that amazing blue knight armor sir?” |
| drop  | 27    | 'Here sir, I found this.', 'How did this get here?', 'Oh, look, somethin’ shiny”, 'Oh hello there brothers! Why whose towel is this this thats left all by its self?', 'Someone left this bag in this pew. Do you know anything about that?', 'Meh. Whats this you have here?', '“Let's stuff it here!” |
| give  | 136   | 'Here sir, I found this.', 'Meh. Whats this you have here?', 'Wow, this looks to be very old. Where is it from?', 'My goodness I wonder how that got there! It sure is pretty isn’t it?”, “Say, where did you get this?!”, “Oh hello there brothers! Why whose towel is this this thats left all by its self?”, “Someone left this bag in this pew. Do you know what it is?”, “Tell me where you found this!”, “What is this? Is this someone’s head?!”, “what is this ston slab” |
| remove| 127   | 'I suppose for today we may as well look at some garbs.’, ‘Hey there! Got time to take a look at something?”, ‘Thank you, sir. What’s with all this silk?”, ‘Hmmm, where am i and why is everything so sharp?’, ‘Ah, squire Lawrence. Did you polish my armor?’, ‘What are you jutting down, sir?’, ‘Hello ratty. I am looking to clean my clothes!’, ‘Yes sir what is this good news? Did you finally get me a new dress?!’, ‘At least my hat is clean.’, ‘Oh, hello there. Pardon my, erm, dusty appearance. It’s been quite journey to get even this far!’ |

Table 10. Top utterances for each verb for the Topic RL model.
B. Game actions within LIGHT

| Action                | Constraints                                                                 | Outcome                              |
|-----------------------|------------------------------------------------------------------------------|--------------------------------------|
| get object            | actor and object in same room. object is gettable.                           | actor is carrying object              |
| drop object           | actor is carrying object. object is gettable.                                 | object is in room                     |
| get object1 from object2 | Actor and object2 in same room. object1 is gettable. object2 is surface or container. object2 is carrying object1. | actor is carrying object1             |
| put object1 in/on object2 | Actor and object2 in same room. object2 is container or surface. actor is carrying object1. | object2 is carrying object1           |
| give object to agent  | Actor and agent in same room. object is a member of actor.                   | agent is carrying object              |
| steal object from agent | actor and agent in same room. object is a member of agent.                   | actor is carrying object              |
| hit agent             | Actor and agent in same room. object is a member of agent.                   | inform agent of attack                |
| hug agent             | Actor and agent in same room. object is a member of agent.                   | inform agent of hug                   |
| drink object          | actor is carrying object. object is a drink.                                 | inform actor of drinking successfully |
| eat object            | actor is carrying object. object is a food.                                  | inform actor of eating successfully   |
| wear object           | actor is carrying object. object is wearable.                                | actor is wearing object               |
| wield object          | actor is carrying object. object is a weapon.                                | actor is wielding object              |
| remove object         | actor is wearing/wielding object. object is wearable or a weapon.            | actor is carrying object              |

Table 11. LIGHT actions and constraints from (Urbanek et al., 2019)
C. LIGHT example

| Persona 1: Village youth | Persona 2: Horse |
|--------------------------|------------------|
| I am a youth who lives in the village. I am adventurous and curious about everything. I get bored easily, so I will always try to slip away from mundane daily tasks to find something more interesting to do. I am smart for my age and a bit smug. | I live on a farm. I work for humans. I like hay. |

**Setting:** Royal stables, Outside Castle - The royal stables hold all of the horses of the noble people living in the castle. They are very well constructed, consisting of expert mason work and fixtures of some sort of heavy, forest-scented wood. Each horse has a large stall, lined with fresh hay replenished by stable hands daily. On the walls of stable, there are tools used to care for and groom the horses, hung on hooks. The stables are lit by lanterns hung throughout the stables.

**Village Youth** This is so boring cleaning out the stables every day
**Horse** Thank you for taking such good care of us
**Village Youth** I’ll be getting you some treats soon as well
**Horse** Mmm. It’s also nice to have your company.
**Village Youth** I wonder what it’d be like to just take one of these horses and roam the countryside
**Horse** Let’s go. It’s been a while since I’ve been taken out to stretch my legs
**Village Youth** Yeah, let’s break out of here. The royalty don’t even care about the horses like I do
**Horse** It’s starting to get dark. I think we will need this lantern.
**Village Youth** Good idea. We’ll need a bundle for sure
**Horse** Maybe the wood for a fire?
**Servant** Yeah, we’ll need a bundle for sure
**Horse** I’ve got the hay. I think we are ready to go. Let’s get out of here

Figure 3. Example episode from the LIGHT dataset, consisting of an environment (location setting, characters with given personas, objects), utterances and game actions. There are 10,777 such human-human gameplay episodes, and a rich world of 663 locations, 1755 characters and 3462 objects.
D. 3-Step Episode Examples

| Self: a cowardly young man in armour | Partner: guard |
|--------------------------------------|----------------|
| **Persona:** I have just been trained as a royal soldier. I am 18 years old and terrified... | **Persona:** I am an immortal bodyguard. The gods have appointed me to protect the king... |
| **Setting:** Trash Heap, Wasteland | **Setting:** Treasure Cavern, Inside Temple |
| A largest trash heap in the kingdom has been burned out so many times that it no longer resembles anything... | Glittering as far as the eye can see the Treasure Cavern is filled with gold, silver, precious gems, ... |
| \(U_0^{\text{player}}\) I'm also in need of a new shield. | \(U_0^{\text{player}}\) Step back intruder! You have no business in the king’s treasure cavern! |
| \(U_0^{\text{env}}\) Squire, my shield fatigues me. | \(U_0^{\text{env}}\) Ha! I’m here to take all of this treasure. End the king’s reign! |
| \(A_0^{\text{env}}\) hug a cowardly young man in armour | \(A_0^{\text{env}}\) get gold |
| \(U_0^{\text{player}}\) Thank you, sir. I needed a hug. | \(U_0^{\text{player}}\) You come to my place and are trying to take my land! Is that what you are doing? You dirty scumbag! |
| \(A_0^{\text{player}}\) Yes. I need you to hold this shield for me. | \(A_0^{\text{env}}\) I will get away with your gold! |
| \(A_0^{\text{player}}\) remove shield | \(A_0^{\text{env}}\) hit bodyguard |

Table 12. Successful 3-step episodes. On the left: the topic-RL agent’s goal was to get the environment agent to remove shield. On the right: the topic-RL agent’s goal was to get the environment agent to hit the topic-RL agent. In both episodes, the topic-RL agent makes natural utterances given the situation that elicit the desired goal in 2 turns.

| Self: cat | Partner: challenger |
|-----------|---------------------|
| **Persona:** I live in the barn of a small farm. I protect the farm from pests... | **Persona:** I am poor and dirty. I hate that I am starving to death... |
| **Setting:** The Dungeon, Inside Palace | **Setting:** Cottage, Countryside |
| The dungeon is in the very most bottom room of the Palace. Many have gone down to the dungeon... | The small cottage was white with two, shuttered windows. It was in the unique shape of a... |
| **Goal:** drop poison | **Goal:** put coin in dinner table |
| \(U_0^{\text{player}}\) What’s that stuff? Smells good. | \(U_0^{\text{player}}\) Oh, what is this? It smells heavenly! |
| \(U_0^{\text{env}}\) That’s smells like the good stuff alright! | \(U_0^{\text{env}}\) Yes it is top quality. |
| \(A_0^{\text{env}}\) give poison to cat | \(A_0^{\text{env}}\) steal moldy bread from peasant |
| \(U_0^{\text{player}}\) I thought so too, well that’s gone. What are you up to? | \(U_0^{\text{player}}\) Excellent! What have you been doing out here on this fine day? |
| \(U_0^{\text{env}}\) I’ve been hiding waiting for the perfect time to make an escape | \(U_0^{\text{env}}\) I have no bread. I have just come to get some rest before moving on. |
| \(A_0^{\text{env}}\) remove bag of herbs | \(A_0^{\text{env}}\) eat moldy bread |
| \(U_0^{\text{player}}\) I thought you might be eating my herb again. | \(U_0^{\text{player}}\) No, but perhaps you can use it to cleanse your bread! |
| \(U_0^{\text{env}}\) I did it, I confess! I stole these precious herbs. | \(U_0^{\text{env}}\) I would love to. I fear I look disheveled. I will wear this blanket to cover my filthy clothes |
| \(A_0^{\text{player}}\) drop bag of herbs | \(A_0^{\text{env}}\) hug peasant |

Table 13. Unsuccessful 3-step episodes. On the left: the topic-RL agent’s goal was to get the environment agent to drop poison. On the right: the topic-RL agent’s goal was to get the environment agent to put coin in dinner table. In both episodes, the topic-RL agent both makes natural utterances given the situation, but does not manage to achieve its goal.