A Additional Notes on Data Preparation

We obtain a rating matrix of 265,905 users and 11,382 movies. We filter the data according to a few criteria:
- Users who watched less than 50 movies are filtered out.
- Movies which are watched less than 50 users are filtered out.
- Movies whose average rates are less than 2 and users who average rates are less than 2 are filtered out.

We also remove some movie sets which are too difficult or too easy to predict based on their distance scores. For example, we filter out movie sets where the cosine similarity of the correct movie and the averaged incorrect movies is less than 0.75. After filtering, the remaining data comprises 5,330 movies, rated by 65,181 users.

We tested different types of embedding features such as movie IDs (i.e., MovieLens's ratings), movie text (i.e., Wiki-text), and knowledge base features (e.g., director's name). The movie ID features turn out to be the best performing for recommendation performance. After training, the model finds reasonable close neighbors; for example, for "Ice Age," the model identifies "Shrek 2," "Shrek," "Monsters Inc.,” and “Finding Nemo” as close.

B Data Collection: Full Description

In our annotation interface, we provide action buttons for workers to click on in order to interact with the system. When a button is clicked, the corresponding system message is shown. For example, if an expert clicks on a movie button to recommend that movie, the system displays a recommendation message to the seeker, using a simple template. Similarly, if a seeker clicks to accept or reject the recommendation, a templated message with the decision is automatically delivered to the expert.

If an expert recommends the correct movie, a seeker accepts the correctly recommended movie, or a seeker rejects an incorrectly recommended movie, they receive a reward (points, which can translate into bonus money if enough points are earned); otherwise, the system encourages them to focus more on the task and get more points. The amount of reward points awarded is calculated based on the similarities between the average of the seeker’s movie set and each candidate movie in the expert’s set, using a softmax. The similarity scores are calculated using the euclidean distance between movie embedding vectors (see Section C).

Overall, a total of 1,034 unique workers created 9,125 dialogues, over a duration of 2.5 weeks.

C Supervised training: Details

This section gives more details about the supervised training phase.

Encoding textual inputs: Textual inputs are encoded differently for the dialogue context and for the movie descriptions. The dialogue history context \( h_t \) for predicting utterance \( x_{t+1} \) comprises the history of all previous utterances \( x_1, \ldots, x_t \). Each utterance is encoded with an LSTM (Hochreiter and Schmidhuber, 1997). The dialogue context is then obtained by averaging over all utterances:

\[
 h_t = \text{AVG}(\text{LSTM}(x_1), \ldots, \text{LSTM}(x_t)) \quad (9)
\]

For the movies, we found that using bags of words instead worked better. We encode each sentence of a movie description as a bag of words, and then average all the resulting representations to obtain \( m_j \), the representation of the \( j \)-th movie:

\[
 E(m_j) = \text{AVG}(\text{BOW}(m_j)) \quad \text{for} \ j \in 1..K \quad (10)
\]

Aligning dialogue context and movie descriptions: we use dot-product attention (Chen et al., 2017) between the dialogue context and each of the movie descriptions:

\[
 c_j = h_t \cdot m_j \quad \text{for} \ j \in 1..K \quad (11)
\]

Generating utterances: Generate The expert can produce two types of utterances, according to whether it is recommending a movie or asking for more input from the seeker. For Recommend, the response is produced by a template: “How about this movie, [MOVIE]?” where [MOVIE] is the movie that the expert is recommending. For Speak, the next utterance is generated by taking the dialogue context history \( h_t \) and the average of all movie representations \( \bar{m} = \text{AVG}(m_1, \ldots, m_K) \), and inputting them into a seq2seq generative model with attention (Bahdanau et al., 2015). The model is then trained to minimize the negative log likelihood of the true next utterance \( x_{t+1} \) according to...
the model distribution \( p_{gen} \):

\[
L_{gen} = -\log p_{gen}(x_{t+1}|h_t, M), \quad \text{where} \quad M = \text{AVG}(m_1, \ldots, m_K) \tag{13}
\]

We include Recommend utterances in the \( L_{gen} \) calculation; as a result, the generation loss is also a partial indicator of other aspects such as Decide and Predict, in addition to the corresponding specific losses (see below).

**Predicting the correct movie to recommend:** \textbf{Predict}  
Let \( y \) denote the correct movie. The prediction module is trained by minimizing the negative log likelihood of \( y \) according to the distribution of a softmax predictor over the \( c_j \) inputs described above:

\[
L_{predict} = -\log p(y|c_1, \ldots, c_K), \quad \text{where} \quad c_j = h_t \cdot m_j \quad \text{for } j \in 1..K \tag{14}
\]

When making a recommendation, the expert recommends the top candidate: \( \arg \max_{c} \{c_1, \ldots, c_K\} \). We also experimented with using a soft representation for the target movie distribution, for example through a softmax over similarities. For instance, in Figure 2, the hard ground-truth movie distribution is \([1, 0, 0, 0, 0]\), and the soft version is \([0.37, 0.15, 0.16, 0.16, 0.15]\). But the hard version always outperformed the soft version in our experiments.

**Deciding when to recommend:** \textbf{Decide}  
The expert needs to decide whether to to recommend a movie or speak to elicit more information. We model this using a two-layer perceptron that takes the movie prediction distribution scores and the dialogue context as input, and predicts whether to make a recommendation or not. Training is conducted by minimizing the negative log likelihood of the ground truth decision:

\[
L_{decide} = p_{MLP}(d_{t+1}|h_t, c_1, \ldots, c_K) \tag{16}
\]

We also experimented with other functions of the movie prediction distribution (e.g., skewness and kurtosis (Mardia, 1970)), but the multi-layer perceptron (MLP) always performed better.

**Supervised loss of the overall system:** The overall objective function of the full supervised system is as follows:

\[
L_{sup} = \alpha L_{gen} + \beta L_{predict} + (1-\alpha-\beta)L_{decide} \tag{17}
\]

where \( \alpha \) and \( \beta \) are weight terms that control the balance between the different objectives and are empirically optimized on the validation set. For the \textbf{Predict} and \textbf{Decide} losses, we use annealing at the beginning of training, with all the weight being given to the \textbf{Generate} loss, and the weights of the other two being gradually increased.
You are a Seeker!

- You’re looking for a movie recommendation. You will be given a list of movies you’ve previously liked. When the expert recommends a movie, you have to agree or disagree the recommendation, based on whether you think it’s a good recommendation.
- You will get bonus for high quality dialogues.
- You can send only one message at a time. You need to finish the chat in 30 minutes.
- After a given number of turns, click DONE to finish the chat.

MOVIES YOU LIKED:

Saying Private Ryan

Saying Private Ryan is a 1998 American epic war film set during the invasion of Normandy in World War II. Directed by Steven Spielberg and written by Robert Rodat, the film is notable for its graphic and realistic portrayal of war, and for the intensity.


Hoop Dreams

Hoop Dreams is a 1994 documentary film directed by Steve James and written by Steven James and Frederick Marx, with Kartemquin Films. It follows the story of two African-American high school students in Chicago and their dream of becoming professional basketball players.

Eyes Wide Shut

Eyes Wide Shut is a 1999 American erotic thriller film loosely based upon Arthur Schnitzler's 1926 novella 'Dream Story'. The film was directed, produced, and co-written by Stanley Kubrick. It was his last film, as he died six days after showing his final rushes.

Big Night

Big Night is a 1996 American motion picture drama with comedic overtones directed by Campbell Scott and Stanley Tucci. Produced by David Kirkpatrick and Jonathan Pikel for the Samuel Goldwyn Company, the film met with critical acclaim both in the United States.

(a) Seeker’s left panel

(b) Seeker’s right panel

You are an Expert!

- The Expert recommends movies to the Seeker via chatting. Please click the button if you figure out what to recommend.
- You will get bonus for high quality dialogues.
- You can send only one message at a time. You need to finish the chat in 30 minutes.
- After a given number of turns, click DONE to finish the chat.

A list of candidate movies to recommend:

Random Hearts

Random Hearts is a 1998 American romantic drama film directed by Sydney Pollack and starring Harrison Ford and Kristin Scott Thomas. Based on the 1984 novel of the same name by Warren Adler, the film is about a police officer and a congressman who discover a love.

Lone Star

Lone Star is a 1996 American mystery film written and directed by John Sayles and set in a small town in Texas. The ensemble cast features Chris Cooper, Kris Kristofferson, Matthew McConaughey, and Elizabeth Peña and deals with a sheriff's investigation.

Out Of Sight

Out of Sight is a 1998 American crime comedy film based on the novel of the same name by Elmore Leonard and directed by Steven Soderbergh. The first of several collaborations between Soderbergh and star George Clooney, it was released on June 26, 1998.

Looking For Richard

Looking For Richard is a 1996 documentary film directed by Al Pacino in his directorial debut. It is both a performance of selected scenes of William Shakespeare's play "Richard III" and a broader examination of Shakespeare's continuing role and relevance.

In The Company Of Men

In the Company Of Men is a 1997 Canadian/American black comedy written and directed by Neil LaBute and starring Aaron Eckhart, Matt Malloy, and Stacy Edwards. The film, which was adapted from a play written by LaBute, and served as his feature film debut.

(c) Expert’s left panel

(d) Expert’s right panel

Figure 8: Interface of our data collection (2): seeker’s and expert’s pages.