

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.
- moves which are watched less than 50 users are filtered out.
- movies which are filmed before 1950 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, \dots, x_t . Each utterance is encoded with an LSTM (Hochreiter and Schmidhuber, 1997). The dialogue context is then obtained by averaging over all utterances:

$$h_t = \text{AVG}(\text{LSTM}(x_1), \dots, \text{LSTM}(x_t)) \quad (9)$$

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 $\mathbb{M} = \text{AVG}(m_1, \dots, m_K)$, 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

Task Description

In this task you will play a movie recommendation game with another user, as either the **expert** or the **seeker**.

- The **seeker**'s goal is to get a movie recommendation. If you play the seeker, you will be given a list of movies.
- The **expert**'s goal is to recommend a movie that the seeker would like, by chatting with them.

Notes:

- The Expert is given a set of movies to choose from. Only one of the movies would be liked by the Seeker. The game ends when the Expert recommends this movie and the Seeker accepts it.
- Both Expert and Seeker will get bonus for **high quality dialogs**.
- You can keep accepting new HITS after you finish your current one, so keep working on it if you like the task!

After a given number of turns, click "DONE" to finish the chat.

When you are ready to start your conversation, click the "**I am ready, continue**" button below

I am ready, continue

Figure 7: Interface of our data collection (1): task description page.

the model distribution p_{gen} :

$$\mathcal{L}_{gen} = -\log p_{gen}(x_{t+1}|h_t, \mathbf{M}), \text{ where} \quad (12)$$

$$\mathbf{M} = \text{AVG}(m_1, \dots, m_K) \quad (13)$$

We include Recommend utterances in the \mathcal{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:

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:

$$\mathcal{L}_{predict} = -\log p(y|c_1, \dots, c_K), \quad \text{where} \quad (14)$$

$$c_j = h_t \cdot m_j \quad \text{for } j \in 1..K \quad (15)$$

When making a recommendation, the expert recommends the top candidate: $\arg \max_c \{r_1..r_K\}$. 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: DECIDE The expert needs to decide whether 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:

$$\mathcal{L}_{decide} = p_{MLP}(d_{t+1}|h_t, c_1, \dots, c_K) \quad (16)$$

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:

$$\mathcal{L}_{sup} = \alpha \mathcal{L}_{gen} + \beta \mathcal{L}_{predict} + (1-\alpha-\beta) \mathcal{L}_{decide} \quad (17)$$

where α and β are weight terms that control the balance between the different objectives and are empirically optimized on the validation set. For the PREDICT and DECIDE losses, we use annealing at the beginning of training, with all the weight being given to the 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 **accept** or **reject** the recommendation, based on whether you think it's a good recommendation.
- You will get bonus for **high quality dialogs**.
- 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.

5 MOVIES YOU LIKED:

Saving Private Ryan

Saving 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. **+**

L.A. Confidential

L.A. Confidential (1990) is neo-noir novel by **James Ellroy**, and the third of his L.A. Quartet series. **James Ellroy** dedicated "L.A. Confidential" to Mary Doherty Ellroy³. The epigraph is "A glory that costs everything and means nothing—Steve Erickson." **+**

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. **+**

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. **+**

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 Filley for the Samuel Goldwyn Company, the film met with critical acclaim both in the United. **+**

(a) Seeker's left panel

SYSTEM:
Successfully matched. Once the correct recommendation is made, you can click the "Done" button to end the chat. Please have enough conversation turns with your partner to give them a sense of the movie preference of your persona. Please carefully read the description and try to speak as if you watched the movies. Each movie will earn a different amount of points, depending how well they match your persona's preferences. If you accept a movie recommendation, you will earn that amount of points. Your goal is to accept the movie with the most points.

Do not just copy the given descriptions into the message but rephrase them.

Seeker: I am looking for recommendation!

Expert: What kinds of movies do you like?

Seeker: I like thriller movies and filmed on around 1990.

Expert:
How about this movie? I recommend this because it's filmed on 19s and crime movie, you may like it!
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**. **+**

Accepted Reject

Seeker: You accepted the recommendation

Expert: Why did you accept the movie?

Seeker: I like the films by George Clooney because he is my favorite actor!

SYSTEM: Oh no! You wouldn't like that movie at all. You only won 15 points out of 38. Try providing more about your persona's movie preferences to Expert

(b) Seeker's right panel

You are an Expert!

- The Expert recommends movies to the Seeker via chatting. Please click **Recommend** button if you figure out what to recommend.
- You will get bonus for **high quality dialogs**.
- 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 **Recommend**

Random Hearts is a **1999** 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 congresswoman who discover. **+**

Lone Star **Recommended**

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. **+**

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Looking For Richard **Recommend**

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

In The Company Of Men **Recommend**

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

SYSTEM:
Successfully matched. Once the correct recommendation is made, you can click the "Done" button to end the chat. Please have enough conversation turns with your partner to get a sense of their movie preference. Please carefully read the description and try to make the most appropriate recommendation. There are 5 possible movies that you can recommend. Each movie will earn a different amount of points, depending how well they match the Seeker's preferences. Your goal is to recommend the movie with the most points.

Do not "Recommend" for the first two turns. Please chat with Seeker to find out what they like. Do not just copy the given descriptions into the message but rephrase them.

Seeker: I like thriller movies and filmed on around 1990.

Expert:
How about this movie?
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**. **+**

Seeker: Why did you recommend this movie?

Expert: I recommend this because it's filmed on 19s and crime movie, you may like it!

SYSTEM: You won 15 points, but the best movie for this round would have earned 38! Try asking more questions next round to recommend a better movie!

Seeker: Seeker accepted your recommendation. I like the films by George Clooney because he is my favorite actor!

Expert:
How about this movie?
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. **+**

Seeker: Why did you recommend this movie?

Expert: It's another 19 movie and Chris Cooper might be also attractive for Seeker like George Clooney!

SYSTEM: Great job! You scored 38, the maximum possible for this round! Try another round if you want to get more points!

(d) Expert's right panel

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