Word Games

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Dialogue and information gathering

- Resolve ambiguity and coordinate through dialogue
- OneCommon: Interactive, symmetric reference game
  - Isolates info gathering (and coordination)
  - Environment (dots) are completely static
  - Dynamism comes from dialogue only
- 20 questions with symmetric information constraints

Previous SotA

- Purely supervised
  - Upper-bounded by performance of demonstrators
- Uncalibrated beliefs: overconfidence
  - Pushes for to select a dot that will not work
- Research goal: Improve supervised models via model-based planning

Fixing strategy with planning

- Prior: Fully supervised neural encoder-decoder
  - Encode past interactions with a neural net
  - Generate what to say with a neural net
  - Brittle strategy, less brittle language
- Next: Model-based planning
  - Choose what to say by imagining how partner would respond
  - Say utterance with best expected outcome
  - Potentially stronger player than expert demonstrations

Challenges in model-based planning

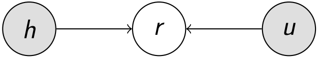
- Partner modeling is hard
  - Variable amount of information in utterances
  - High entropy demonstration strategies
- Multi-turn planning
  - Accuracy of planning depends greatly on the partner model
  - Errors from the partner model will compound over time[1]
- Single-turn planning
  - Removes compounding errors
  - Must optimize a dialogue progress heuristic: uncertainty reduction
  - Requires belief with uncertainty
  - Still requires accurate partner model[2]
- Research question: Can we improve partner modeling for planning by simplifying partner responses?

[1] Errors in planning will be a result of compounding partner model errors on top of search error.

[2] Belief is function of dialogue history and partner model.

Planning

- Partner response depends on utterance and conversation history
  - First history $h_0 =$ dots you can see
  - History h_t, utterance u, response r
  - Next history $h_{t+1} = (h_t, u, r)$



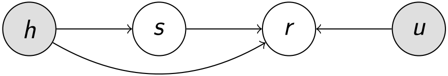
- Plan by imagining partner response r

$$\min_u \mathbb{E}_{p(r|h,u)} [\text{Cost}(h, u, r)]$$

  - Produce utterances from prior model and rerank
- Cost should approximate dialogue progress
  - Goal of dialogue is information gathering and coordination
  - Focus on information gathering
- Cost should be a function of belief

Planning with Belief

- Introduce belief $p(s \mid h)$
  - State s is what dots partner can also see
  - Response model $p(r \mid h, u, s)$ now has more conditioning



- Incorporate belief in planning

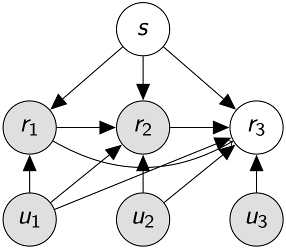
$$\min_u \mathbb{E}_{p(r \mid h,u,s)p(s \mid h)} \left[\text{Uncertainty}(p(s \mid h, u, r))\right]$$

- Obtain belief posterior via belief update

$$p(s \mid h, u, r) = \frac{p(r \mid h, u, s)p(s \mid h)}{\sum_s p(r \mid h, u, s)p(s \mid h)}$$

Partner response model

- Static latent state s: which dots do they also see
  - Alternative: actual field of view
  - Pick s that is observed during training so we can keep all models supervised
- Uniform prior $p(s)$ over 7 choose 4 dots partner also sees
- Partner response model $p(r_t \mid u_{1:t}, r_{1:t-1}, s)$
  - History $h_t = (u_{1:t-1}, r_{1:t-1})$



Response model: Informativity

- Example exchange
  - Action: Do you see a red dot?
  - Observation: No, but I see a blue one.
- Utterances are multifaceted
  - Responses contain more information than asked
  - New information injected by partner, not constrained
  - Difficult to model new information
- Introduce informativity as another variable
- Make worst-case assumption about informativity **during planning**
  - Assume a limit on number of bits transmitted
  - Conservative lower bound on uncertainty reduction / dialogue progress

Incorporating informativity

- Add partner-level informativity i to response model $p(r \mid h, u, s, i)$
  - Determines partner willingness to give more information
  - More information improves game-play
- Introduce uncertainty set over $i \in [\text{low}, \text{high}]$

$$\min_{u} \min_{i \in [\text{low},\text{high}]} \mathbb{E}_{p(r \mid h,u,s,i) p(s \mid h)} \left[\text{Uncertainty}(p(s \mid h, u, r)) \right]$$

- Optimize worst-case informativity $i = \text{low}$
- Constrain informativity in response via discrete coding

Limiting informativity with discrete coding

- Compress response into discrete code $z \in [K]$
- Use variational information bottleneck (VIB)[3]
- Optimize mutual information objective[4]
  - Focus code z on response to new information introduced by utterance u
  - But limit the information shared with response r and history h

$$\max_{\theta} I(z, u; \theta) - \beta I(z, r; \theta) - \gamma I(z, h; \theta)$$

- Lagrange multipliers β, γ
- Plan with response model $p(z \mid h, u, s)$ instead of r

[3] Alemi et al. (2016)

[4] Closely related to the approach of Li and Eisner (2019)

Belief update

- Performing the belief update with z instead of r would lose information
- Use original model $p(r \mid h, u, s)$ to update belief?
  - May run into original possible issue of poor calibration
- Learn another discrete representation of r that does not aim to disentangle
  - Need as baseline for model with z
  - Likely adequate when combined with mentions

Summary

- Goal: Show (partner) model-based planning works for dialogue with purely supervised components
  - Single-turn planning for limiting compounding model errors
  - Belief-based heuristic for measuring dialogue progress
  - Response coding for conservative planning

Belief unit tests

Belief calibration: check belief dynamics on static conversations.

- Diminishing returns
  - Ask the same question twice (rephrased) should not change belief
  - Asking about the same dot should have diminishing uncertainty reduction
- Updates are conservative
  - Require multiple positive answers to diff questions before being certain about a dot
- High probability after confirming all neighbouring dots

Extrinsic evaluation: Selfplay

Compare to prior work (without belief)

- Success rate
  - Should be higher
- Efficiency (success / num turns)
  - Possibly higher because more success, but more turns
- Number of repeated mentions
  - Should be higher if policy more conservative

Questions

1. How do we measure belief calibration?
   - Unit tests examining conservativity of beliefs
2. How calibrated are the belief updates using various response representations?
   - Too much information (ie full word response) results in low probability to responses, which results in a large belief update = optimism
   - Not enough information = conservative
3. How well can we produce a range of utterances to search over?

Hypothesis

- High information response representation
  - Calibrated policy (assuming accurate model)
  - Hard to model responses
- Low information response representation
  - Conservative policy (assuming accurate model)
  - Easy to model responses
- Prefer conservative + accuracy response model over inaccurate response model

Response representations

- Words in response
  - Full response
  - First k words of response
- Dot mentions
  - All dot groups mentioned in response
  - First k dot groups mentioned in response
- Discrete encoding
  - K-means cluster of sentence rep
  - Specialized cluster (information bottleneck)
- Continuous encoding
  - Sentence rep
  - Specialized encoding (information bottleneck)

Experiments

- Evaluate response representations on unit tests and selfplay
- Binary matrix of representation x unit test property
- Main unit tests
  - Diminishing returns
  - Conservativity
  - High probability
- Representations
  - Words
  - Dots
  - Learned (discrete, continuous)
- Consider highest and lowest information representations, work our way in
  - Hypothesize that best point is in between first dot and all dots

Experiment 1

Evaluate word response models on belief unit tests

- Belief representations
  - Full response
  - First k words
- Hypothesis
  - Full response will fail all unit tests
  - First k will fail high probability test. Too conservative due to missing information
- Outcomes
  - Full is too optimistic, motivating different representations for exploring more conservative belief updates
  - Full is conservative, which is a success. Method is general, just need to try it on other datasets
  - First k is too optimistic. This would indicate information hypothesis is wrong, and potential issues with any other subsequent representation approach.

Experiment 2

Evaluate dot response models on belief unit tests

- Belief representations
  - All dot mentions
  - First k dot mentions
- Hypothesis
  - These might do okay on unit tests
  - First $k = 1$ often captures responses
- Outcomes
  - First k fails due to optimism, implies info hypothesis is wrong.
  - First k succeed, which gives an indication that a learned structured generalization has promise. If all also succeeds, same.

Experiment 3

Evaluate learned discrete response models on belief unit tests

- We can tune the amount of information via number of clusters
- If training goes well, should be able to get a fine-grained view of information - conservativity tradeoff
- Belief representations
  - K-means cluster on pretrained sentence rep
  - Specialized cluster[5]
- Hypothesis
  - K-means might be pretty competitive, depending on sentence representations
  - K-means should be conservative, since untuned sentence reps may not pick up relevant information
  - Specialized clusters should do better than k-means with naive sentence rep
- Outcomes
  - If any of these succeed, selfplay and try on another dataset
  - If fail, end of line

[5] Li and Eisner (2019)

End

Full planning details

- Given history h, we need to chose an action a by optimizing heuristic utility
$$\min_a C(h, a)$$
- Cost c = -information gain + utterance + pragmatic cost
  - IG: Reduce uncertainty
  - Utterance cost: Can't send a full paragraph
  - Pragmatic cost: Want utterance to be accurate
- Ideally would estimate and optimize future reward directly
  - Heuristic approximation of future reward U
  - Limited-horizon planning to minimize impact of model error

Expected information gain

- Maximizing expected information gain equivalent to minimizing uncertainty

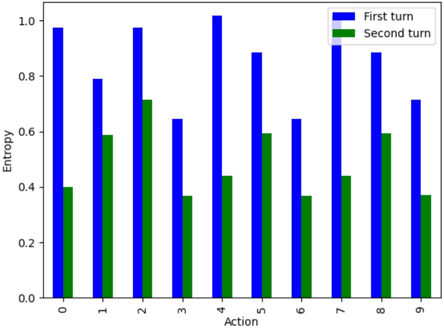
$$\min_u \sum_r \sum_s \underbrace{p(r \mid h, u, s)}_{\text{response model}} \underbrace{p(s \mid h)}_{\text{belief}} \text{Uncertainty}(\underbrace{p(s \mid h, u, r)}_{\text{new belief}})$$

Experiments

- Mutual Friends
  - Augment rule-based (prior work) to optimize info gain
  - After OneCommon: Add neural on top
- OneCommon
  - Use attributes = raw mention configurations
    - Need belief / info gain / LR weights
    - How to deal with redundancy? (i.e. correlation between features)
  - Learn latent refinement on top of mention configurations

Information gain issues

- Best info gain could be to ask the same question twice
- Usual fix: Limit to asking once only
- Would be nice to have a principled way to deal with correlated features though



- Second turn after taking action with lowest entropy

Related work: 20 questions

- Padmakumar and Mooney (2020)
  - Attribute-based classification (string heuristic to map to description) + activate learning about attributes
  - Info gain (on top of binary unweighted logistic regression) as feature for RL policy
- Yu et al. (2019)
  - Question-based classification (attributes)
  - Learn weights of features
  - Do not consider feature correlations
- More interesting language, symmetric setting
- Learn weights, account for correlation
- Symmetry, deal with unexpected features

End

Concerns

- Would a large LM solve all of this?
  - Fine tune on small onecommon dataset, are there still repeats?
  - Unlikely to solve strategy / over optimistism

Expected Information Gain

$$IG(h, a) = H(i \mid h) - \mathbb{E}_{p(o \mid h,a)} \left[H(i \mid h, a, o) \right]$$

$$\mathbb{E}_{p(o \mid h,a)} \left[H(i \mid h, a) \right] = \sum_{o} \sum_{i'} p(o \mid h, a, i) p(i \mid h) H(i \mid h, a, o)$$

- Equivalent to minimizing expected uncertainty after receiving a response
- Cite Yu et al, White et al

Citations I

Alemi, A. A., Fischer, I., Dillon, J. V., and Murphy, K. (2016). Deep variational information bottleneck. *CoRR*, abs/1612.00410.

Li, X. L. and Eisner, J. (2019). Specializing word embeddings (for parsing) by information bottleneck. *CoRR*, abs/1910.00163.

Padmakumar, A. and Mooney, R. J. (2020). Dialog policy learning for joint clarification and active learning queries. *CoRR*, abs/2006.05456.

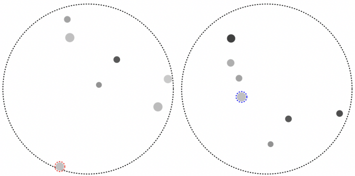
Yu, L., Chen, H., Wang, S. I., Artzi, Y., and Lei, T. (2019). Interactive classification by asking informative questions. *CoRR*, abs/1911.03598.

Games

Friends of agent A:

Name	School	Major	Company
Jessica	Columbia	Computer Science	Google
Josh	Columbia	Linguistics	Google
...	...	...	...

A: Hi! Most of my friends work for Google
B: do you have anyone who went to columbia?
A: *Hello?*
A: I have Jessica a friend of mine
A: and Josh, both went to columbia
B: *or anyone working at apple?*
B: SELECT (Jessica, Columbia, Computer Science, Google)
A: SELECT (Jessica, Columbia, Computer Science, Google)



Human A's view   Human B's view

Human B: three light grey dots in a diagonal line
Human A: i dont have that but i have a black dot neer the top to the right, the only black dot in the circle
Human B: i have two black dots. find something else
Human A: ok i have a light grey dot by itself at the bottom to the left. right on the line
Human B: how big is it
Human A: its one of the bigger ones
Human B: okay just pick it then
Human A: ok
Human B: SELECT blue
Human A: SELECT red

Mutual Friends and OneCommon

Issue: Poor neural reasoning

From Mutual Friends: Neural + Human

- A: Know anyone who likes chess?
- B: None of my friends like chess.
- (conversation continues)
- A: Crocheting?
- B: None like crocheting.
- A: Chess?
- B: None like chess either, haha.

Sample of prior work in model-based planning

- 20 questions (Yu et al., 2019; Padmakumar and Mooney, 2020)
  - Sym: Assymmetric questioner + answerer
  - Turns: Multi-turn game
  - Lang: Closed class answers (observations)
  - Heur: Expected info gain heuristic
- EVPI (**??**)
  - Sym: Assymmetric questioner + answerer
  - Turns: No interaction, single turn game
  - Lang: Open
  - Heur: Expected utility heuristic
- RSA reference game (**?**)
  - Sym: Symmetric
  - Turns: Multi-turn game
  - Lang: Symbolic language
  - Heur: Bounded depth search

Conditioning in partner modeling

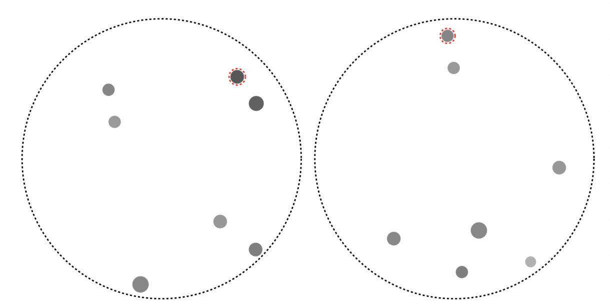
- Assuming conditional independence $p(o \mid h, a, y) = p(o \mid a, y)$ is harmful
- If you ask the same question twice, your belief changes both times!
  - $p(\text{yes} \mid h = \emptyset, a = \text{red dot?}, y)$ can vary depending on the latent y
  - $p(\text{yes} \mid h = (\text{red dot?}, \text{yes}), a = \text{red dot?}, y) = 1$, since we just asked!
- 'Questions with correlated answers' and deficient observation model lead to uncalibrated beliefs, and therefore poor strategy
- Contribution: relax independence assumption
  - Let past obs vote on current one (weighted by action similarity)
  - Probably solved by Transformers[6]

[6] Copy attention, depends on amount of data

Example dialogue 1: Overconfidence

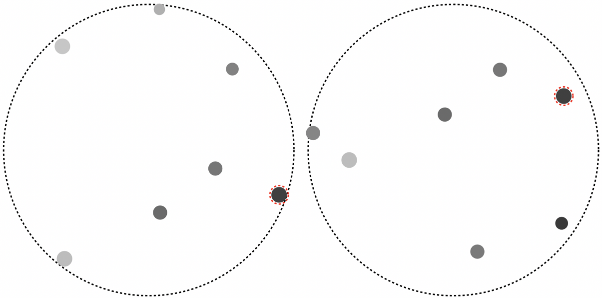
0	i have a large black dot , it 's not the same size , but it is not the darkest
1	Mine is the darkest
0	i see it . i think it is the one .
1	I have multiple dark dots so I am not sure
0	i have a large black dot , it is in the center
1	I have a large dot in the lower part with a dark smaller dot at seven o'clock
0	is the black dot the darkest ? if so click it
1	I have three the same darkness
0	pick the lightest one
1	Ok but our odds are not good.
0	pick the light one

Example dialogue 2: Overconfidence



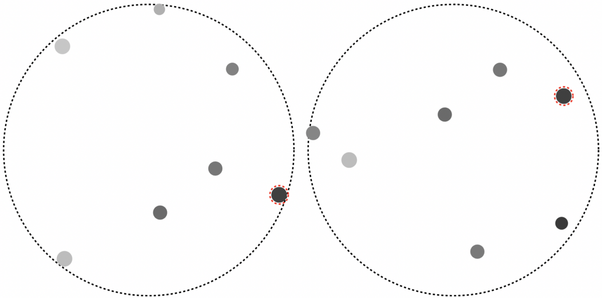
0	i have two dark dots , one on top and slightly smaller than the other
1	i see it. pick the top one?
0	ok

Example dialogue 3: Good humans



1	I have a large black dot by itself
0	I see a large, very dark dot on the edge of my screen (so I won't be able to see anything to its right). Can you see anything on the left of your large black dot?
1	Yes, my large dark dot is on the edge of the right side
0	Ok, to the left of the dark dot, and slightly above it, do you see a slightly-smaller, slightly lighter dot?
1	yes

Example dialogue 3: Good humans



0	and then far above (and a bit to the right of) that lighter one, do you see a slightly smaller, identically colored dot?
1	No, the first lighter dot is the closest dot to the top of mine
0	Okay. what do you see to the left of that lighter dot?
1	A slightly darker dot that is below it just a bit
0	ok, I think we're in the same place. Let's click that original, blackest dot
1	Okay sounds good