

Word Games

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Dialogue

- ▶ Communication is rarely unambiguous
 - ▶ Ambiguity resolution through dialogue
 - ▶ Clarification questions
- ▶ Interactive, symmetric reference games
 - ▶ Isolates ambiguity resolution
 - ▶ Both give and request information

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?*

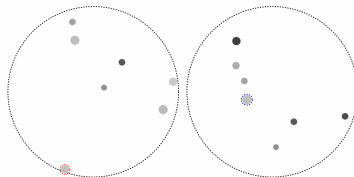
A: I have Jessica a friend of mine

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.

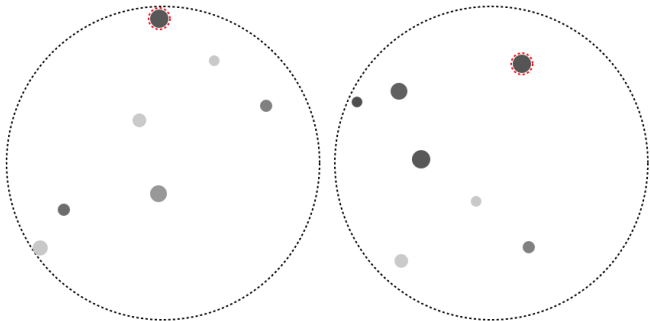
Issue: Poor neural reasoning



Agent 0: human || 1: human

0	1
0	1 I see a large grey dot with a smaller black dot right below it
1	0 is the smaller black dot to the right and below
2	1 No, it is slightly to the left and below
3	0 Might not be the same one. Do you have a lot of dots in a fairly vertical conformation
4	1 I have three dots in a kinda vertical line with different shade of gray but close in size
5	0 Is the middle dot curved to the left or right a little bit?
6	1 the middle dot is slighly to the left of the other two and is also a little bit darker than the rest
7	0 Yes pick that middle dot

Issue: Poor neural reasoning



Agent 0: pragmatic_confidence || 1: human

	0	1
0	0	i have one large black dot by itself . do you have it ?
1	1	Yes, I do have that.
2	0	let 's pick that one
3	1	ok
4	0	ok

Issue: Scaling rule-based

- ▶ Rule-based text generation and understanding is somewhat viable for Mutual Friends
 - ▶ Very optimistic selection, but can be tuned
- ▶ Continuous and spatial nature of OneCommon makes writing rules difficult
 - ▶ Size, color, and positions all continuous
 - ▶ Descriptions are relative

Current approaches: Two extremes

- ▶ Neural encoder-decoder
 - ▶ Encode past interactions with a neural net
 - ▶ Generate what to say with a neural net
 - ▶ Brittle strategy, less brittle language
- ▶ Rule-based
 - ▶ Encode past interactions in a table
 - ▶ Use rules for what to say next
 - ▶ Nonparametric lookup of utterances
 - ▶ Brittle language, less brittle strategy
- ▶ Meet in middle with interpretable planning + neural language

A dialogue turn

- ▶ Engaging in dialogue requires
 - ▶ Inference: What do I know? How do I represent it?
 - ▶ Planning: What should I do and say?
- ▶ Formulate as model-based optimization
 - ▶ Plan what to say through a simple model of our partner
 - ▶ Model of partner conditions on past information

Problem setup

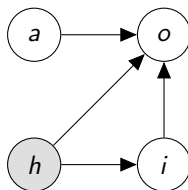
- ▶ Goal: Mutually select the same item as partner
 - ▶ Row in knowledge base, dot
 - ▶ Coordinate through dialogue
- ▶ Given history h , we need to choose an action a by optimizing value

$$\max_a U(h, a)$$

- ▶ Utility $U = \text{information gain} + \text{utterance} + \text{pragmatic cost}$
 - ▶ IG: Entropy reduction of item selection probability
 - ▶ Utterance cost: Can't send a full paragraph
 - ▶ Pragmatic cost: Want utterance to be accurate
- ▶ Represent h, a using attributes
 - ▶ Columns of knowledge base, spatial configuration of dots

Information Gain

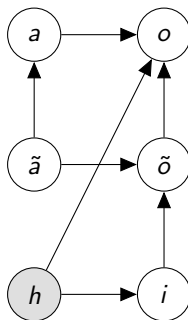
- ▶ A good action should move us closer to game success
- ▶ Game success depends on our knowledge of our partner's context
- ▶ Requires
 - ▶ Belief distribution over selection item given history $p(i | h)$
 - ▶ Partner response model $p(o | h, a, i)$
- ▶ Represent a turn as



- ▶ Language and planning coupled

Decoupling language and planning

- ▶ Compress actions a and observations o into language and abstract representations \tilde{a}, \tilde{o}
 - ▶ Language is high dimensional, redundant, and inefficient for planning
- ▶ Represent a turn as



- ▶ Abstract observation $\tilde{o} \perp\!\!\!\perp h \mid \tilde{a}, i$

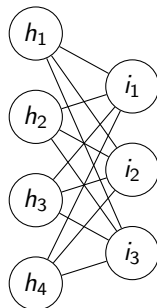
State and belief: Representation

- ▶ History: whether attributes have been confirmed $h \in \{0, 1\}^N$
- ▶ Items: $i \in [M], N \gg M$
- ▶ Logistic regression with attributes as features

$$p(i | h) = \frac{\exp(\sum_n \psi(h_n, i))}{\sum_{i'} \exp(\sum_n \psi(h_n, i'))}$$

$$\psi(h_n, i) = W_{ni} 1(h_n(i))$$

- ▶ Generate per-game $W = f(\text{context})$ from neural network
 - ▶ Many correlated features
 - ▶ How to (conditionally) sparsify?
- ▶ Dialogue = online feature selection



Attributes

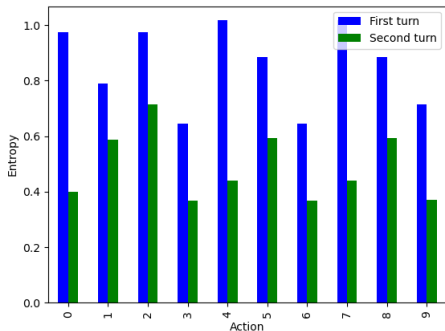
- ▶ Mutual Friends
 - ▶ Combinations of columns of knowledge base
 - ▶ Name, major, company
- ▶ OneCommon
 - ▶ Which dots are mentioned
 - ▶ Need to learn lower-level attributes
- ▶ Numerical reasoning?

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



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
- ▶ Less interesting language in both

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 optimism

End

Value: Information Gain

- ▶ drop slide
- ▶ Picture would be much better here...
- ▶ Value = expected information gain

$$IG(h, a) = H(i | h) - \mathbb{E}_{p(o|h,a)} [H(i | h, a, o)]$$
$$\mathbb{E}_{p(o|h,a)} [H(i | h, a)] = \sum_o \sum_{i'} p(o | h, a, i) p(i | h) H(i | h, a, o)$$

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

Citations I

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.