

# 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
  - ▶
- ▶ Uncalibrated beliefs: overconfidence
  - ▶ Pushes for to select a dot that will not work
- ▶ Research goal: Improve purely 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
  - ▶ Random strategies
- ▶ Multi-turn planning
  - ▶ Accuracy of planning depends greatly on the partner model
  - ▶ Errors from the partner model will compound over time
- ▶ Single-turn planning
  - ▶ Removes compounding errors
  - ▶ Optimize a dialogue progress heuristic: uncertainty reduction
  - ▶ Requires belief
- ▶ Use what dots partner also sees as belief

# Planning

- ▶ Plan by imaging partner response

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

- ▶ Utterance  $u$ , response  $r$ , history  $h$
- ▶ Utility should approximate dialogue progress
  - ▶ Goal of dialogue is information gathering and coordination
  - ▶ Focus on information gathering
- ▶ Utility a function of belief

# Planning with Belief

- ▶ Introduce belief state  $p(s \mid h)$ 
  - ▶ State  $s$  is what dots partner can also see
- ▶ Incorporate belief in planning

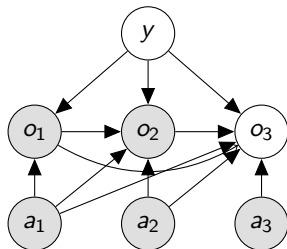
$$\max_u \mathbb{E}_{p(r|h,u,s)p(s|h)} [\text{Certainty}(p(s \mid h, u, r))]$$

- ▶ Obtain

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

## Belief model

- ▶ Static latent quantity  $y$ : which dots do they also see
  - ▶ Alternative: actual field of view
- ▶ Actions  $a_t$ , observations  $o_t$ 
  - ▶ Prior work: yes/no questions (20 questions)
  - ▶ OneCommon: unrestricted language for both
- ▶ Uniform prior  $p(y)$  over 7 choose 4 dots partner also sees
- ▶ Observation model  $p(o_t \mid a_{1:t-1}, o_{1:t-1}, y)$ 
  - ▶ Pick  $y$  that is observed during training
  - ▶ Ideally fully supervised
  - ▶ Prior work<sup>1</sup> makes naive Bayes assumption  $p(o_t \mid a_t, y)$



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<sup>1</sup>Yu et al. (2019); Padmakumar and Mooney (2020)



# Belief update

- ▶ Interaction history  $h_t = (a_0, o_0, \dots, a_t, o_t)$  contains all previous actions and observations
- ▶ Given an initial belief  $p(y | h_t)$  + next action/observation, obtain next belief via

$$p(y | h_t, a_{t+1}, o_{t+1}) \propto \underbrace{p(o_{t+1} | h_t, a_{t+1}, y)}_{\text{observation model}} p(y | h_t)$$

- ▶ Belief calibration depends on accuracy of observation model

# Observation model

- ▶ 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 due symmetric roles
  - ▶ Very difficult to model new information
- ▶ Simplifying assumption: only model response, not new information
  - ▶ Update belief state afterwards by pretending we asked corresponding question
  - ▶ Allows reduction to 20 questions / assymetric role
- ▶ Supervised training needs observed  $o, h, a, y$ 
  - ▶ Main question: How to extract responses  $o$ ?

# Response extraction

- ▶ Heuristic: Use repeated mentions from response
  - ▶ Do you see a red dot? Yes, the one next to the blue one?
- ▶ Generalization: TBD
- ▶ Recap: we have
  - ▶ Belief over shared dots  $p(y \mid h)$
  - ▶ Observation model  $p(o \mid h, a, y)$
  - ▶ Update  $p(y \mid h, a, o)$
  - ▶ Reduced to asymmetric case by extracting response only
- ▶ Next: Single-turn planning

# Planning: Use prior work in asymmetric setting

- ▶ Given history  $h$ , we need to choose an action  $a$  by optimizing heuristic utility

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

- ▶ Utility  $U = \text{information gain} - \text{utterance} - \text{pragmatic cost}$ 
  - ▶ 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

$$\min_a \sum_o \sum_y \underbrace{p(o \mid h, a, y)}_{\text{observation model}} \underbrace{p(y \mid h)}_{\text{belief}} \text{Uncertainty}(\underbrace{p(y \mid h, a, o)}_{\text{new belief}})$$

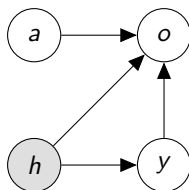
# Summary

- ▶ Goal: Extend methods from 20 questions to symmetric, language setting
- ▶ Extract relevant information from partner utterances
- ▶ Use explicit belief state + single-turn planning heuristic

End

# Information Gain

- ▶ A good action should decrease uncertainty
- ▶ Requires
  - ▶ Belief distribution over selection item given history  $p(y | h)$
  - ▶ Partner response model  $p(o | h, a, y)$
- ▶ Represent a turn as

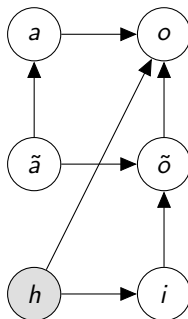


- ▶ Language and planning coupled



# 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



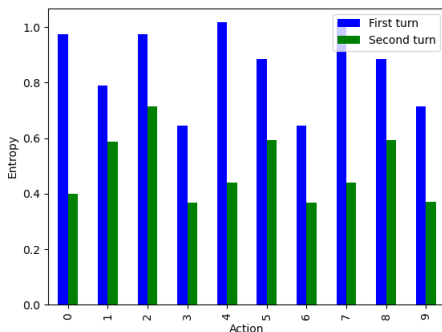
- ▶ Abstract observation  $\tilde{o} \perp\!\!\!\perp h \mid \tilde{a}, i$

# 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 optimism

End

# Expected Information Gain

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

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



# Citations I

- 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?*

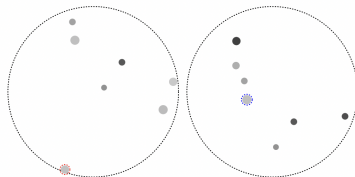
A: I have Jessica a friend of mine

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: Asymmetric questioner + answerer
  - ▶ Turns: Multi-turn game
  - ▶ Lang: Closed class answers (observations)
  - ▶ Heur: Expected info gain heuristic
- ▶ EVPI (??)
  - ▶ Sym: Asymmetric 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<sup>2</sup>

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<sup>2</sup>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

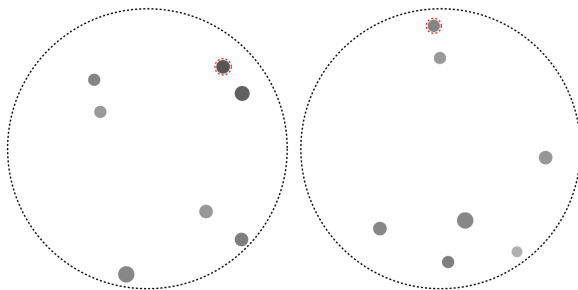
1 I have three the same darkness

0 pick the lightest one

1 Ok but our odds are not good.

0 pick the light one

## Example dialogue 2: Overconfidence

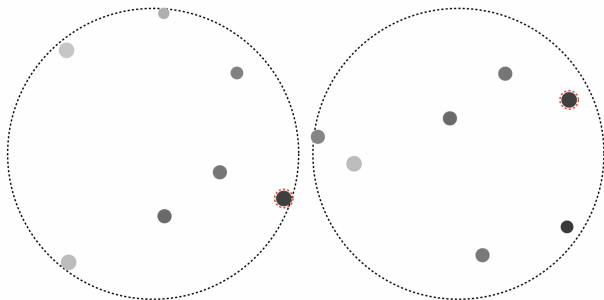


0 | i have two dark dots , one on top and slightly smaller than the other

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?

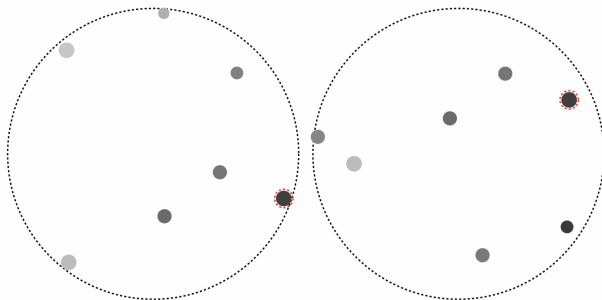
1 Yes, my large dark dot is on the edge of the right side

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   |