Word Games

J Chiu

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Motivation: Why OneCommon

- OneCommon is all about referring expressions (resolving / generating)
- Focus on improving reference resolver, text has more noise
- Improve generation using reference resolver
- Goal: Reduce as much learning as possible to reference resolver
- Impact: Need to carry over to referring expressions in other settings

Current OneCommon Performance

- How can we improve the reference resolver?
  - Best model gets 93% accuracy 78% exact match
  - Human is 96% accuracy 87% exact match
  - Does fine-tuning pretrained models improve accuracy of reference resolver?
  - How can we close the gap?
- Would a better reference resolver result in a better selection model?
  - Yes, training on true refs gives 99% accuracy selection model
  - Best model currently at 83%, humans at 91%
- Does fine-tuning pretrained models improve round-trip of reference generator?
  - Generation second priority
  - Likely over-fitting

Improving Reference Resolution

- Resolving multiple dots
  - Likely not enough data
  - Gather more data with more ambiguity, i.e. dots all have the same size and color? Would this transfer?
- Architectures that are more biased towards composition
  - DIORA
  - Transformers? (possibly with attention constraints)
- Reasoning explicitly about past references
  - Belief state / checklist
  - Pragmatic inference via mutual exclusivity (check if anything is referenced multiple times)
- Coreference
  - Unfamiliar, need further research
  - How often does this happen?
- Dialogue acts
  - Pragmatics of resolution vary based on dialogue act
  - Confirmation repeats vs new references

3 Challenges

- Modular models
  - Dialogue model = local meaning representation - belief state - dialog act - utterance generation
  - Various works supervise particular parts then leave others to be implicitly learned through neural nets
  - Results in very task-specific architectures
  - Can we break down tasks to allow for more component sharing across different tasks, as well as semi-supervised learning?
- Less complicated meaning representations
  - Meaning representations vary in granularity
  - Can we learn a minimal task-specific subset of a meaning representation formalism?
- Adapting to partners
  - Partner model allows forward modeling, learned over a multiple round game or repeated games
  - Adapt opaque neural model or hierarchical bayesian model?
- Better reference resolution / referring expression models?
  - Dialogue games are often data scarce and out of domain
  - Can we use models that are more sensitive / with stronger biases?

Natural Language Interaction

- Interaction (through language) is important
  - Cannot fully automate every task, i.e. task-oriented or information seeking dialogues require human input
  - Must handle diverse non-expert human input, although input may map to a low-dimensional manifold
  - High levels of ambiguity must be resolved via interaction
- Interaction (through language) is hard
  - Human input is expensive, so supervision is limited
  - In order to make certain problem aspects tractable, must make sacrifices in other areas (toy domain = out of distribution for pretrained models)
- What are the main challenges in interaction, and what are the tradeoffs of different approaches?

Types of Dialogue Games

- Task-oriented: Wizard of Oz (WoZ)
  - Tseng et al. (2019): Wizard obtains task from human then executes it.
- Deliberation / reference / signal
  - Udagawa and Aizawa (2019): Visual reference game with latent translated views. Each player gets a different petri dish view of the same underlying game board, and players must select the same object on the board.
- Information seeking / inquiry
  - Yu et al. (2019): WoZ-style answer providing where asker does not know exact question. Latent true question (to all), WoZ must answer
- Persuasion / negotiation
  - Lewis et al. (2017): Negotiation over an observed set of item with latent utilities for each agent.

Types of Dialogue Games

In all cases, the game can be (indirectly) solved by resolving a latent variable

- When is this tractable, and why do no new methods do this?
- New (ie basically all) methods rely on supervision
- If they do not, it is because the game has a trivial solution

Talk with Nori

- Planning doesnt really exist in most dialogue games, the games are too simple
- Referring expressions in OneCommon can be outliers in terms of complexity. Complexity in real world image+text data comes from large noun classes and relatively simple phrases. Still seems like an interesting testbed though, and maybe there is an argument for OneCommon, despite its artificial difficulty (maybe people like talking about stars?).
- Latent variable models for adaptation still seem interesting, should read Hawkins' work.

Types of Dialogue Games: Latent goals and strategy

What are the latent variables in each type?

- Task-oriented
  - Latent task slots
- Deliberation / reference / signal
  - Varies per game
- Information seeking / inquiry
  - Infer true question, find answer
- Persuasion / negotiation
  - Infer utilities, exploit

Types of Dialogue Games: Latent goals and strategy

- Tasks must be interesting enough so that latent quantities cannot be inferred with a single utterance, reducing them to single turn games
  - High degree of ambiguity / distractors or large number of slots to fill (combinatorial)
- Break down latent quantities and use heuristics to make assumptions on structure
  - For example, choosing an ordering of WoZ slots: When choosing a restaurant, first figure out time, then cuisine, and finally price
  - Will likely remain task-specific
- What other parts can we learn?

Belief State Tracking

- The incremental inference procedure is known as belief state tracking (BST)
- Local semantics are aggregated into belief state, which informs high-level strategic decisions
- Seems difficult to learn language, high level strategy, belief state updating, and low level parsing at the same time
- Ablate how structure influences each of these

Language Games

- Games offer a testbed for the development of methods
  - Allow designers to control difficulty and simplicity
- Allowing interaction through language increases the population of players

Meaning reps

- In full generality, this problem is often encountered in hierarchical RL
  - Less bleak in the language gamesetting
  - Games are often very simple and can be constrained to small horizons, for example He He engineered a parser and policy that basically solves the negotiation task
- Many text-specific meaning representations (MR) to choose from
  - Many are too complex
  - Can we leverage existing MRs to learn a minimal task-specific representation that balances utility and expressivity?

Contributions

- Under a unified Bayesian game perspective of dialog games, present formulations for different classes of dialogs: signaling, negotation?
- Provide pipelined variational Bayesian framework for learning to play dialog games from offline data, with and without granular annotations
- Good results

Tasks

- Task-oriented dialogue: Multi-WoZ
- Negotation: Deal-or-no-deal
- Reference: OneCommon
- Information-Seeking: Birds

Generation under uncertainty

- Lemon et al. (2010)

Citations I

Lemon, O., Janarthanam, S., and Rieser, V. (2010). Generation under uncertainty. In *Proceedings of the 6th International Natural Language Generation Conference*. Association for Computational Linguistics.

Lewis, M., Yarats, D., Dauphin, Y. N., Parikh, D., and Batra, D. (2017). Deal or no deal? end-to-end learning for negotiation dialogues. *CoRR*, abs/1706.05125.

Tseng, B., Rei, M., Budzianowski, P., Turner, R. E., Byrne, B., and Korhonen, A. (2019). Semi-supervised bootstrapping of dialogue state trackers for task oriented modelling. *CoRR*, abs/1911.11672.

Udagawa, T. and Aizawa, A. (2019). A natural language corpus of common grounding under continuous and partially-observable context. *CoRR*, abs/1907.03399.

Citations II

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