

# Incremental Pragmatics and Emergent Communication

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# Groundedness in Emergent Communication

- Roughly: one-to-one correspondence between vocabulary tokens and real-world attributes;
- Useful for interpretability;
- Might be a prerequisite to productivity (cf. Kottur, et al. 2017).

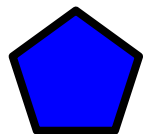
$$G(u) = \frac{\max_a(C(u, a))}{C(u)} \quad (1)$$

$$G(P) = \sum_{u \in V_A} \frac{G(u)}{|V_A|} \quad (2)$$

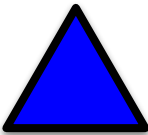
# Prior Work on Groundedness in Emergent Communication

- “Emergence of Grounded Compositional Language in Multi-Agent Populations” (Mordatch & Abbeel 2017);
- “Learning Cooperative Visual Dialog Agents with Deep Reinforcement Learning” (Das, et al. 2017);
- “Natural Language Does Not Emerge ‘Naturally’ in Multi-Agent Dialog” (Kottur, et al. 2017).

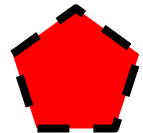
# Task & Talk



Task: [Color, Shape]  
Ans: [Blue, Pentagon]



Task: [Color, Style]  
Ans: [Blue, Solid]



Task: [Shape, Style]  
Ans: [Pentagon, Dashed]

Q-Bot: Turn 1

A-Bot: Turn 1

Q-Bot: Turn 2

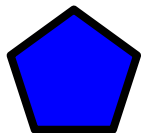
A-Bot: Turn 2

X → 1 → Y → 6

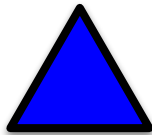
X → 1 → Z → 11

Y → 6 → Z → 12

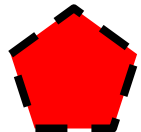
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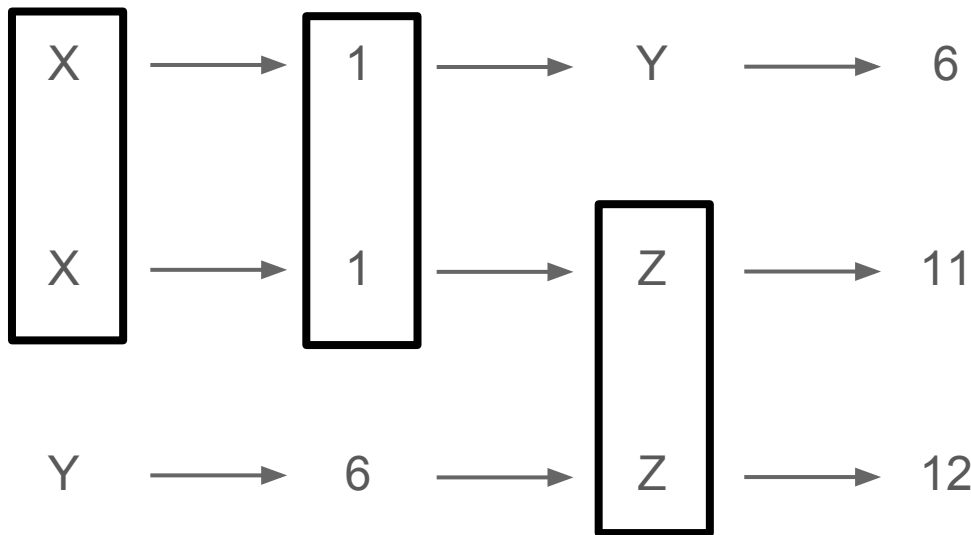


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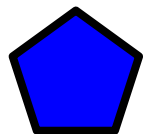


Task: [Shape, Style]  
Ans: [Pentagon, Dashed]

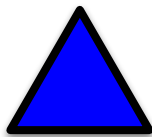
Q-Bot: Turn 1    A-Bot: Turn 1    Q-Bot: Turn 2    A-Bot: Turn 2



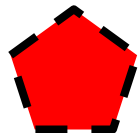
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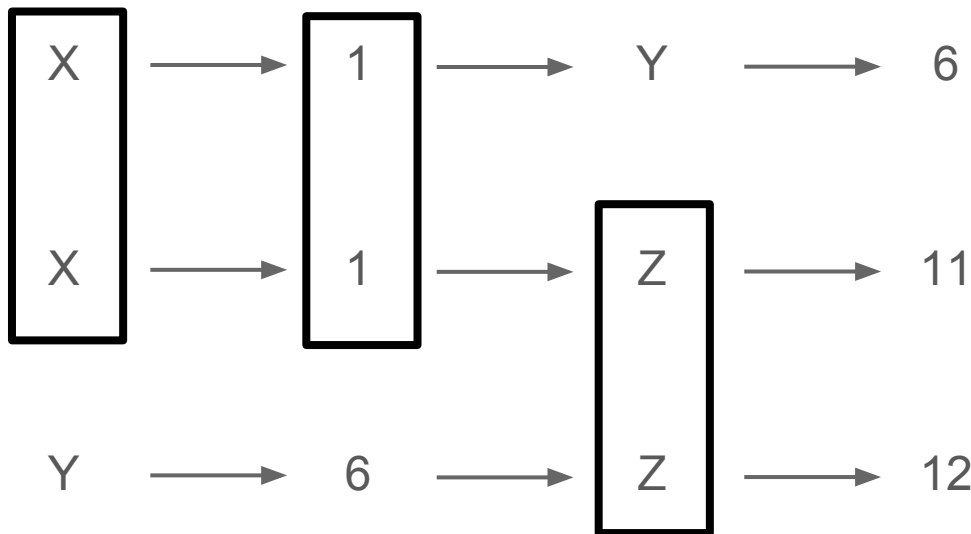


Task: [Color, Style]  
Ans: [Blue, Solid]



Task: [Shape, Style]  
Ans: [Pentagon, Dashed]

Q-Bot: Turn 1    A-Bot: Turn 1    Q-Bot: Turn 2    A-Bot: Turn 2



(Idealized example: the models aren't really doing this!)

# Problems with *Task & Talk*

- Reduces to “4x4 Variant” after Q-Bot’s first turn;
- Proposed changes to task design:

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	Original (Kottur et al., 2017)	4x4 Baseline	4x4 Multitask
Q-BOT speaks	✓	✗	✗
Q-BOT observes $G$	✓	✓	✗
Utility function $U(\hat{w})$	✗	✗	✓
Pragmatic model	✗	✗	✓
Curriculum learning	✗	✗	✓
Number of tasks	3	1	3
Number of referents	64	16	16
Vocab size $ V_A $	4	4	8

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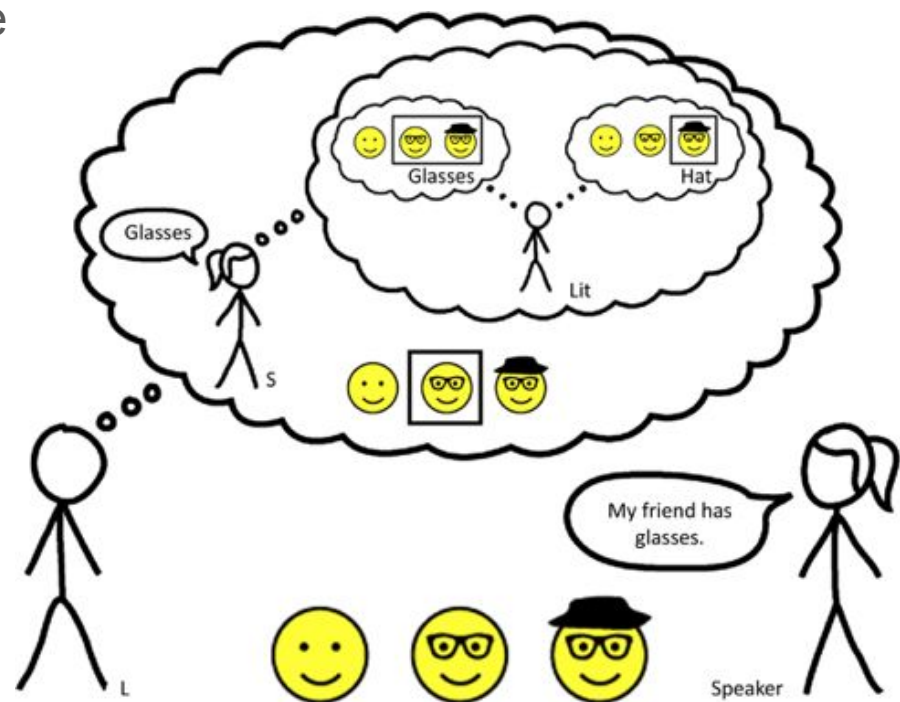
# 4x4 Multitask

- Mixture of tasks: (shape) and (shape, color) both acceptable;
- Curriculum learning: one-attribute tasks presented first;
  
- Might expect that grounded communication would emerge in this scenario, but it doesn't with tabular Q-learning or REINFORCE;
- Perhaps we're missing some communication mechanism...



# Rational Speech Acts (Frank & Goodman 2012)

- Recursive reasoning process between speakers and listeners about alternative utterances and referents;
- Meant to capture the **cooperative principle**: be concise, truthful, informative, relevant, etc.;
- Enforces an injective mapping between referents and utterances.




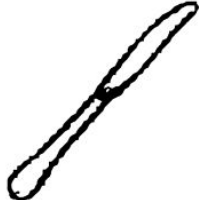


# Incremental Pragmatics

Incremental pragmatics is a well-motivated mechanism of human language processing (Sedivy, et al. 1999).

Target: “Touch the yellow bowl.”

Eye-tracking after “yellow” favors the yellow comb rather than the bowl because of the contrast effect.

yellow 		yellow 
	+	
pink 		

# Incremental RSA (Cohn-Gordon, et al. 2018)

Base RSA agent:                    [[utterance]](world)

Base incremental RSA agent:      [[partial utterance]](world)

...where [[partial utterance]](world) denotes the fraction of possible utterance continuations which are consistent with the world state.

$$P(a_t \mid s_t^A) \propto \pi_A(a_t \mid s_t^A; \theta_A) \cdot \mathbb{E}_{s_0^Q} \left[ \pi_Q(\hat{w} \mid s_0^Q; \theta_Q) \cdot U(\hat{w}) \right]$$

# Model and Results

We train tabular Q-learning and REINFORCE agents on modified *Task & Talk*. The incremental pragmatic model achieves near-perfect groundedness.

Mean groundedness scores across 100 iterations:

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	4x4 Baseline	4x4 Multitask
Tabular Q-Learning	0.153	0.181
Tabular Q-Learning (MC)	0.151	0.182
REINFORCE	0.150	0.188
Pragmatic REINFORCE	0.153	<b>0.874</b>

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# Future Work

- Ablations on task modifications
- Wider domain for evaluation on held-out data
- Evaluating time-course of grounding:
  - Does RSA speed up training? (It weakly constrains the search space.)
  - Why do tokens become ungrounded? What is the effect of batch size?
- Comparison to memory efficiency models of productivity (cf. Yang 2016)
- Evaluate human performance on this task (MTurk experiment!)

Thank you!