Cognitive modeling

Probabilistic models 2 – Communication and probabilistic models of pragmatics

Reading: Goodman and Frank: Pragmatic language interpretation as probabilistic inference

15-01-2020

Last lecture

- Conventionalized meaning
  - The meaning of morphemes that we agree on as a community

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- Conventionalized meaning
  - The meaning of morphemes that we agree on as a community
- Topics for exam:
  1. Basic concepts from probability: Conditional probability, Bayes' rule, the law of total probability, random variable...
  2. Basic probability distributions mentioned in exercise/class (Bernoulli, Uniform, Normal, Gamma)
  3. The structure of Bayesian models (what is prior? what is posterior?)
  4. Language of thought and Probabilistic Context-Free Grammar
  5. Acquisition of conventionalized meaning as a Bayesian update

Going beyond conventionalized meaning

- Words and sentences are used in communication
- Pragmatics – research on the role of communication in comprehension & production
- Cognitive modeling & pragmatics - combination of mainly probabilistic models with insights from the theory of pragmatics

Goal of this lecture

- Discuss examples showing that communication affects comprehension & production
- Discuss an approach that can explain this role of communication
- Assess cognitive models of pragmatics

1. Some examples on the role of communication in comprehension and production

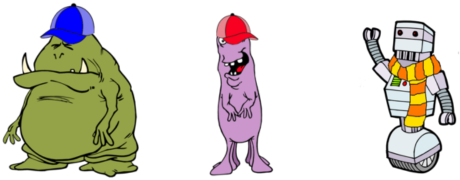
2. Communication as update on beliefs (RSA)

3. Cognitive modeling and pragmatics

These creatures might attack:

Reference game: Monsters and robots

These creatures might attack:



You see:

Messages that could be used:

- What message do you send?

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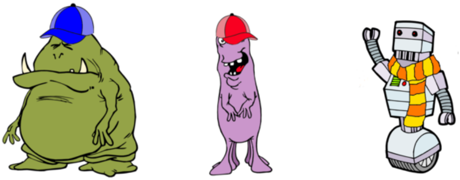

You see:

Messages that could be used:

- What message do you send? In red circle

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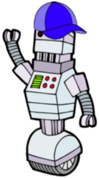

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  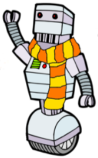

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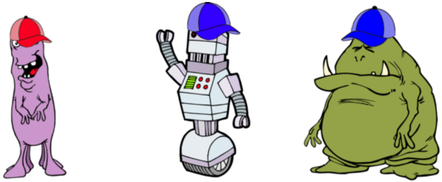

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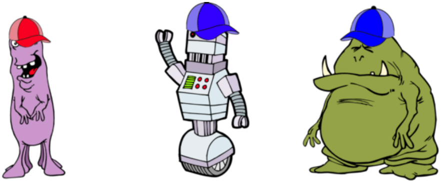

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Messages that could be used:

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Monsters and robots

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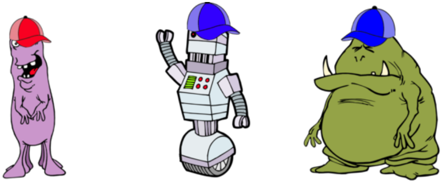

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Messages that could be used:

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Monsters and robots

These creatures might attack:

Monsters and robots

These creatures might attack:

You receive:

Messages that could be used:

- What monster is attacking?

Monsters and robots

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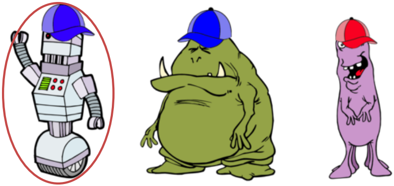

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Monsters and robots – production, reasoning

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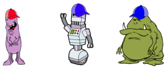

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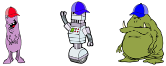

You see:

Messages that could be used:

- You could send  or .
-  can mean two things and could be misinterpreted.
-  means only one thing (the actual attacking monster).

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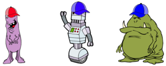

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⇒ You send .

- Communication principle: Use expression that is true and more informative than other true alternatives.

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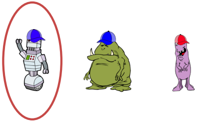

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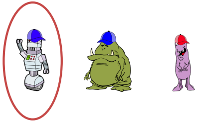

You receive:

Messages that could be used:

-  can correspond to the robot or the green monster.
- If your friend wanted to indicate the green monster, she would have sent  (due to the Communication principle from the previous slide)
- She did not, so she did not mean that.

⇒ Hence, she must have meant the robot.

Monsters and robots – comprehension, reasoning

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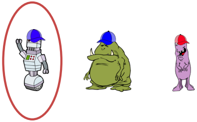

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- Communication principle: Speaker uses expression that is true and more informative than alternatives.

Do we use communication principles? Do we reason about other people using them?

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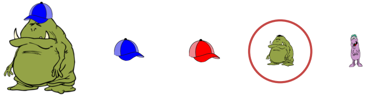

- Around 80% responses select 'green monster' as their message.

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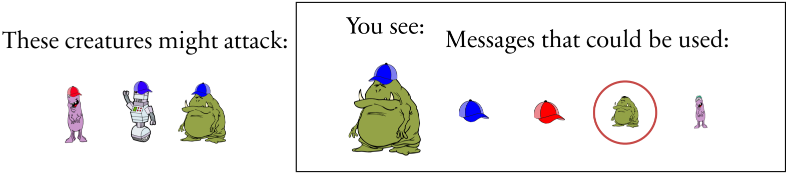

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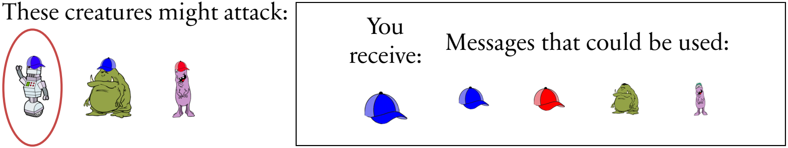

- Around 80% responses interpret ‘blue cap’ as the robot.

Franke and Degen (2016). Reasoning in Reference Games. PLoS ONE 11.

Do we use communication principles? Do we reason about other people using them?

Yes.

- *more than half* – 50% or more
- If you correctly answer more than half of the questions on the exam, you will pass the course.
- $\langle 51\%, 100\% \rangle \Rightarrow$ you passed

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A: Did you read all of the assigned papers?

B: I read more than half of them.

- Literal message: *more than 50% (so possibly all)*
- Communicated message: *more than half but not all*

Do we use communication principles? Do we reason about other people using them?

Typical Gricean reasoning pattern:

- The speaker has said she has read more than half the papers.
- She could have said that she read all the papers. That would be more informative.
- She didn't say this. She must have had a good reason not to say something that is more informative.
- The most obvious reason is because she knows this more informative message to be false.
- She is thus implicating that she did not read all the papers.

Grice, Logic and Conversation, 1974

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Communication as update on beliefs

There are two perspectives:

- Speaker: Which message am I going to send?
- Listener: Which meaning is true?

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Speaker's prior beliefs:

Which message will I send?

$\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$

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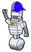
Listener's prior beliefs: Which fact is true?	Speaker's prior beliefs: Which message will I send?
	
$\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$	$\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$

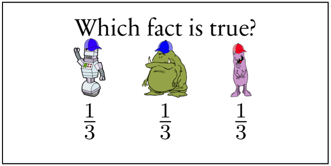
- $P_L($  $) = P_L($  $) = P_L($  $) = \frac{1}{3}$
- $P_S(\text{blue cap}) = P_S(\text{red cap}) = P_S(\text{green m.}) = \frac{1}{3}$

Communication as update on beliefs (cont.)

Which fact is true?

$\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$

Communication as update on beliefs (cont.)



- Speaker and Listener are rational.
- After hearing the message, Listener rationally updates his beliefs.
- To rationally update beliefs amounts to generating the right conditional probabilities $P_L(fact|message = m)$
- What is $P_L(fact|message = m)$?

Communication as update on beliefs (cont.)

What fact is true?

$\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$

What messages can be sent?

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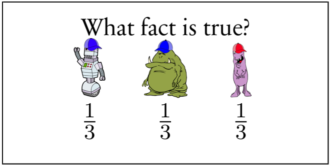
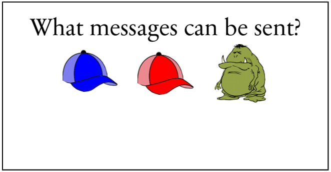
$\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$

What messages can be sent?

For each message m_i, we want to see $P(fact|m_i)$





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- Bayes' rule + LOTP:

$$P_{L_0}(fact|message) = \frac{P(message|fact) \cdot P(fact)}{\sum_i P(message|fact_i) \cdot P(fact_i)}$$

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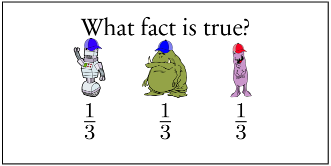
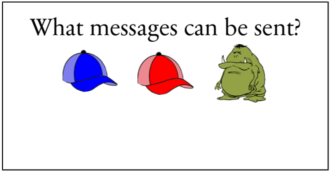
  - Let us expand the denominator:

$P_{L_0}(fact|message) =$

$P(msg|fact) \cdot P(fact)$ / $P(msg|fact =$  $) \cdot P(fact =$  $) + P(msg|fact =$  $) \cdot P(fact =$  $) + P(msg|fact =$  $) \cdot P(fact =$  $)$





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  - Result of application of conditional probability:
  - $P_{L_0}(fact = \;|message = green\_monster) = P_L(fact = \;|message = red\_cap) = 1$
  - $P_{L_0}(fact = \;|message = blue\_cap) = P_L(fact = \;|message = blue\_cap) = \frac{1}{2}$

Communication as update on beliefs (cont.)

Speaker's prior beliefs:

What message will I send?

$\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$

Possible facts:

Communication as update on beliefs (cont.)

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Possible facts:

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$$P_{L_0}(fact|message) = \frac{P(message|fact)P(fact)}{\sum_i P(message|fact_i)P(fact_i)}$$

- Speaker's update:

$$P_{S_1}(message|fact, \alpha) = \frac{e^{\alpha \cdot log(P_{L_0}(fact|message))}}{\sum_i e^{\alpha \cdot log(P_{L_0}(fact|message_i))}}$$

- Assume $\alpha = 1$; $P_{S_1}(message|fact) = \dfrac{P_{L_0}(fact|message)}{\sum_i P_{L_0}(fact|message_i)}$

Communication as update on beliefs (cont.)

- $P_{L_0}(fact =$  $| message = blue\_cap) = P_L(fact =$  $| message = blue\_cap) = \frac{1}{2}$
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- Assume $\alpha = 2$; $P_{S_1}(message|fact, \alpha) = \dfrac{e^{2 \cdot log(P_{L_0}(fact|message))}}{\sum_i e^{2 \cdot log(P_{L_0}(fact|message_i))}}$;

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Communication as update on beliefs (cont.)

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  $P_{S_1}(message = green\_monster|fact =$  $) = .8$
- Assume $\alpha = 5; P_{S_1}(message = green\_monster|fact =$  $) = .97$

Communication as update on beliefs (cont.)

- Assume $\alpha = 1; P_{S_1}(message|fact, \alpha) = \dfrac{P_{L_0}(fact|message)}{\sum_i P_{L_0}(fact|message_i)}$

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Possible facts:

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- Bayes' theorem (for pragmatic listener):

$$P_{L_2}(fact|message) = \frac{P_{S_1}(message|fact)P(fact)}{\sum_i P_{S_1}(message|fact_i)P(fact_i)}$$

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- $P_{S_1}(message = blue\_cap|fact =$  $) = 1$
- $P_{S_1}(message = blue\_cap|fact =$  $) = \frac{1/2}{1+1/2} = \frac{1}{3}$
- $P_{S_1}(message = green\_monster|fact =$  $) = \frac{1}{1+1/2} = \frac{2}{3}$

Possible facts:

$\frac{1}{3}$ $\frac{1}{3}$ $\frac{1}{3}$

- Bayes' theorem (for pragmatic listener):

$$P_{L_2}(fact|message) = \frac{P_{S_1}(message|fact)P(fact)}{\sum_i P_{S_1}(message|fact_i)P(fact_i)}$$

- $P_{L_2}(fact =$  $|message = blue\_cap) = \frac{3}{4}; P_{L_2}(fact =$  $|message = blue\_cap) = \frac{1}{4}$
- $P_{L_2}(fact =$  $|message = green\_monster) = 1$

Taking stock

- We assume:

  Communication is a rational update on beliefs (probabilities)

  Listener updates his beliefs rationally and believes that the speaker does so as well

  Speaker updates her beliefs rationally and believes that the listener does so as well

- By one iteration of belief updates, we predict that the speaker would use 'green monster' in the relevant case in 2/3 of cases with $\alpha = 1$.

Goodman et al. (2016). Pragmatic Language Interpretation as Probabilistic Inference, Trends in Cognitive Science 20

(The Rational Speech Act Theory)

Question

- How good are we at this sort of social recursion?
  (Cognitive modeling meets pragmatics)

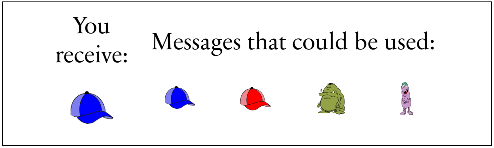
1. Some examples on the role of communication in comprehension and production
2. Communication as update on beliefs (RSA)
3. Cognitive modeling and pragmatics

These creatures might attack:

You receive:

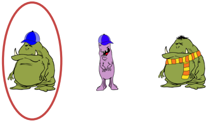
Messages that could be used:

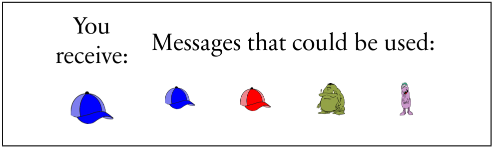
These creatures might attack:



- What monster is attacking?
- To get it right, one needs to apply Bayesian reasoning twice (red circle)

These creatures might attack:





- What monster is attacking?
- To get it right, one needs to apply Bayesian reasoning twice (red circle)

These creatures might attack:

You receive: Messages that could be used:

- What monster is attacking?
- To get it right, one needs to apply Bayesian reasoning twice (red circle)
- In experiment, most people chose the right option only slightly more than 50% (guessing)

Franke and Degen (2016). Reasoning in Reference Games. PLoS ONE 11.

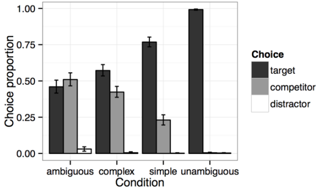
- Let's assume P_{L_2} and P_{S_1}

$$P_{S_1}(message|fact, \alpha) = \frac{e^{\alpha \cdot log(P_{L_0}(fact|message))}}{\sum_i e^{\alpha \cdot log(P_{L_0}(fact|message_i))}}$$

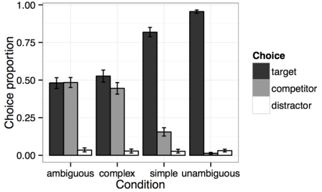
$$P_{L_2}(fact|message) = \frac{P_{S_1}(message|fact)P(fact)}{\sum_i P_{S_1}(message|fact_i)P(fact_i)}$$

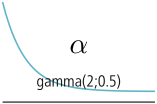
- How does the model capture production and comprehension data?

Comprehension



Production





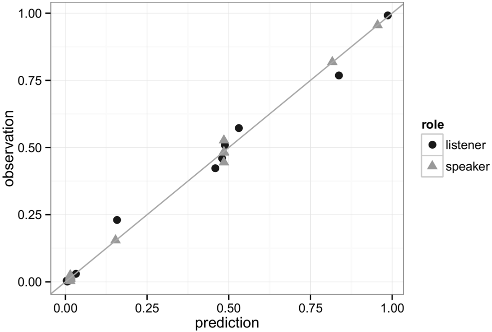
$$p = \mathbf{RSA}(\alpha)$$

$$\text{Binomial}(p, n)$$

Binomial(p, n) - number of successes from n trials, each trial success with prob. p

The model is not solved analytically; rather, we sample from posterior and inspect the samples (Kruschke, 2011, Doing Bayesian Data Analysis, ch. 7) (cf. exercise)

Bayesian model, results



- $\alpha = 2.5$
- Fit of the model: $r = 0.997$

- Impressive fit of the model but to *aggregated data*
- Are individuals rational speakers and listeners (S_1, L_2)?
- Be wary:
  - Simpson's paradox:

Dr. Hibbert:

	Heart	Band-Aid
Success	70	10
Failure	20	0

Dr. Nick:

	Heart	Band-Aid
Success	2	81
Failure	8	9

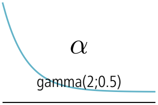
  - Interpretation of aggregated data usually at odds with cognitive models (also here)

We assume that a speaker is S_0, S_1 or S_2 (similarly for listeners) with probability P^D

$$P^D \sim \text{DirichletDist}(1, 1, 1)$$

$$\tau_j \sim \text{Categorical}(P^D)$$

$$\alpha$$



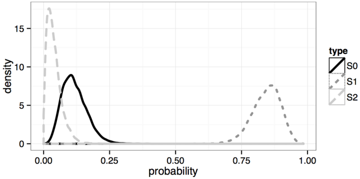
$$p = \textbf{RSA}(\tau_j, \alpha)$$

$$\text{Binomial}(p, n)$$

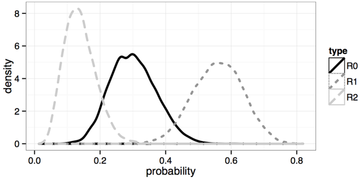
The model is not solved analytically; rather, we sample from posterior and inspect the samples (Kruschke, 2011, Doing Bayesian Data Analysis, ch. 7) (cf. exercise)

Bayesian model II, results

Posterior distributions of P^D



(a) speaker



(b) listener

- For comprehension, complex Bayesian model strongly preferable

Acquisition

Do sub-populations struggle with pragmatic reasoning?

- *some* – a few or more
- If you correctly answer some of the questions on the exam, you will pass the course.
- $\langle \approx 10\%, 100\% \rangle \Rightarrow$ you passed

Acquisition

Do sub-populations struggle with pragmatic reasoning?

- *some* – a few or more
- If you correctly answer some of the questions on the exam, you will pass the course.
- $\langle \approx 10\%, 100\% \rangle \Rightarrow$ you passed

A: Which horses jumped over the fence?

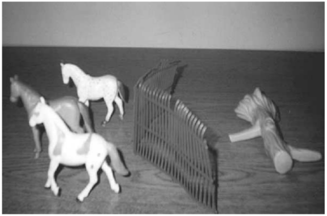
B: Some of the horses jumped over the fence.

- B's literal message: *some, and possibly all, horses jumped over the fence*
- Communicated message: *some but not all horses jumped over the fence*

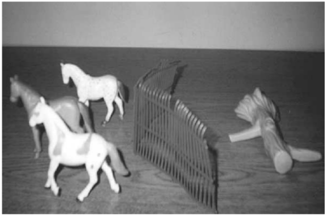
- How does the acquisition of *some* proceed?

Papafragou et al. (2013). Scalar implicatures. Cognition 86

Acquisition

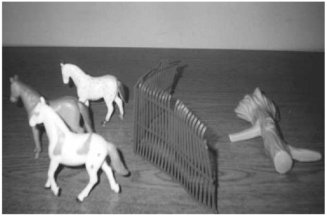


Acquisition

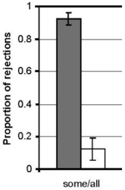


- Some of the horses jumped over the fence.

Acquisition



- Some of the horses jumped over the fence.

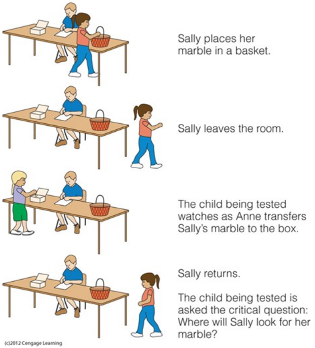


white bar – children (5 yo); grey bar – adults

Why do children fail in pragmatic reasoning?

- They are bad at reasoning about other people's mental stage

  They lack the theory of mind (ToM)
- cf. false-belief task, which young children usually fail
- Correlation between adult sub-populations and ToM?



Why do children fail in pragmatic reasoning?

- Problems with the ToM explanation
- 5 yo usually fully capable of false-belief tasks, yet failing pragmatic reasoning
- The acquisition of pragmatic reasoning differs per item

Conclusion

- Production and comprehension is affected by communication situation, which enriches meaning
- Pragmatic reasoning modeled as Bayesian update (pragmatic speakers and listeners)
- Cognitive models that assume (just) pragmatic speakers and listeners account for aggregated data
- To account for individual data, a richer model better
- The richer model assumes individual differences wrt pragmatic reasoning

Topics to know

- Rational Speech Act Theory (literal listener, pragmatic speaker, pragmatic listener)
- Reference games
- Basic probability distributions (Gamma, Binomial…)
- Modeling aggregated vs. individual data