

Pragmatic reasoning in large-scale NLP systems

Christopher Potts

Stanford Linguistics

University of Tübingen, December 3, 2020

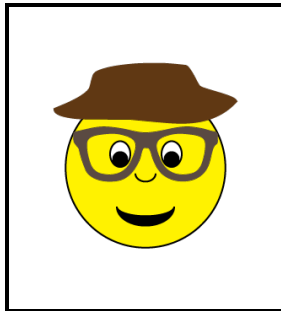


Informativity in context

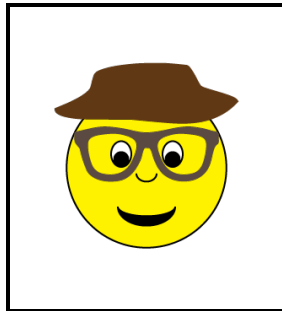
Generating referring expressions



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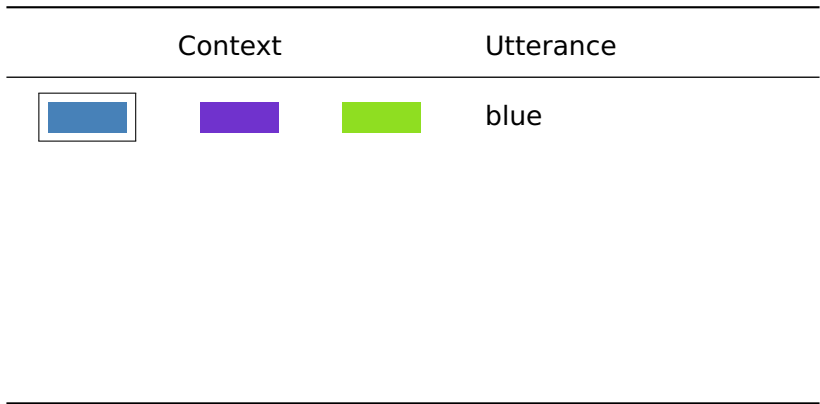


“The guy with a hat”

Interpreting complex descriptions







Stanford Colors in Context corpus
(Monroe et al. 2017)

Interpreting complex descriptions



Stanford Colors in Context corpus
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Interpreting complex descriptions

	Context		Utterance
			blue
			The darker blue one













Stanford Colors in Context corpus
(Monroe et al. 2017)

Interpreting complex descriptions

	Context	Utterance
		 blue
		 The darker blue one
		 dull pink not the super bright one

Stanford Colors in Context corpus
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Interpreting complex descriptions

	Context	Utterance
		 blue
		 The darker blue one
		 dull pink not the super bright one
		 Purple

Stanford Colors in Context corpus
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Interpreting complex descriptions

	Context	Utterance
		 blue
		 The darker blue one
		 dull pink not the super bright one
		 Purple
		 blue

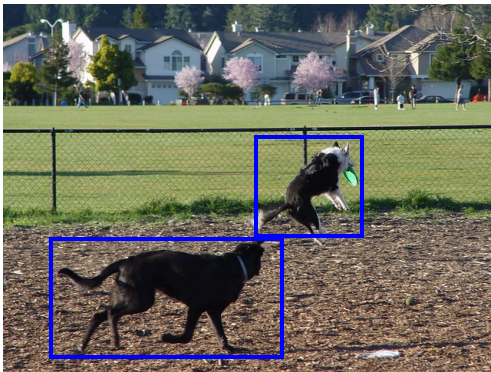
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Discriminative image labeling



Mao et al. 2016

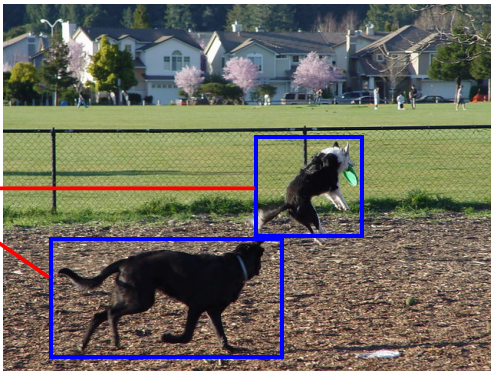
Discriminative image labeling



Mao et al. 2016

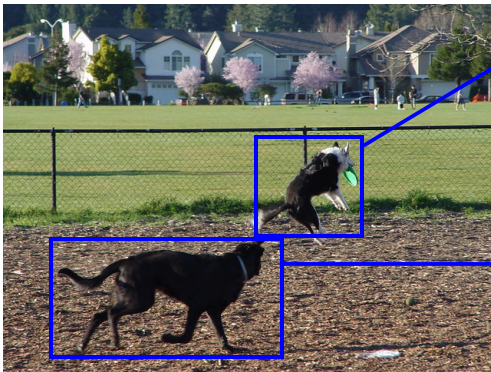
Discriminative image labeling

Dog



Mao et al. 2016

Discriminative image labeling



A little dog jumping and catching a frisbee

A big dog running

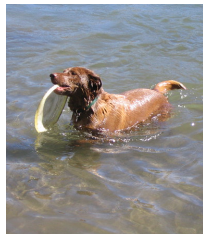
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Discriminative image captioning



Vedantam et al. 2017; Cohn-Gordon et al. 2018

Discriminative image captioning



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Issue-sensitive image captioning



Issue-sensitive image captioning



QUD: *Party politics?*

Issue-sensitive image captioning



QUD: *Party politics?*

Democratic former
president Barack Obama

Issue-sensitive image captioning



QUD: *Party politics?*

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QUD: *Race and ethnicity in
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QUD: *Complete description?*

Issue-sensitive image captioning



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QUD: *Complete description?*

Barack Obama wearing a blue tie, blue shirt, . . .

Summarization

Tennis champion Serena Williams wobbled into the Third Round of the Australian Open on Thursday.



Serena Williams advances to Australian Open Third Round.

Ongoing work with Hanson Lu and Reuben Cohn-Gordon

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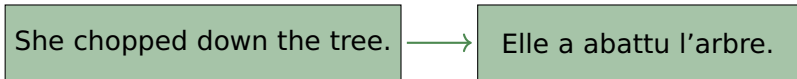
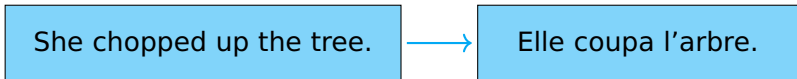
Sports Champion advances in tournament.

Golfer Lydia Ko eliminated from British Open after finishing 12 over par.

Williams wobbled on Thursday.

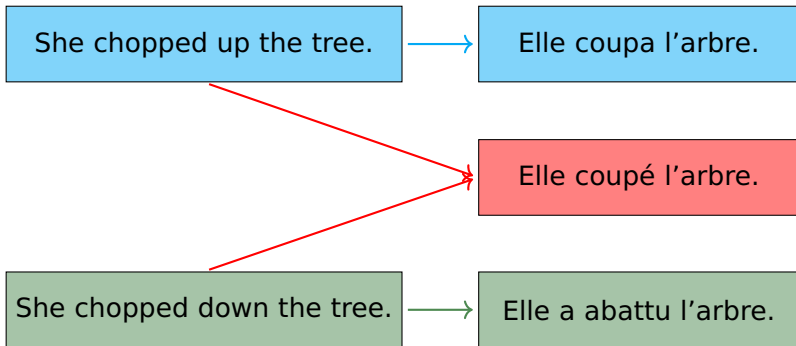
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Machine translation



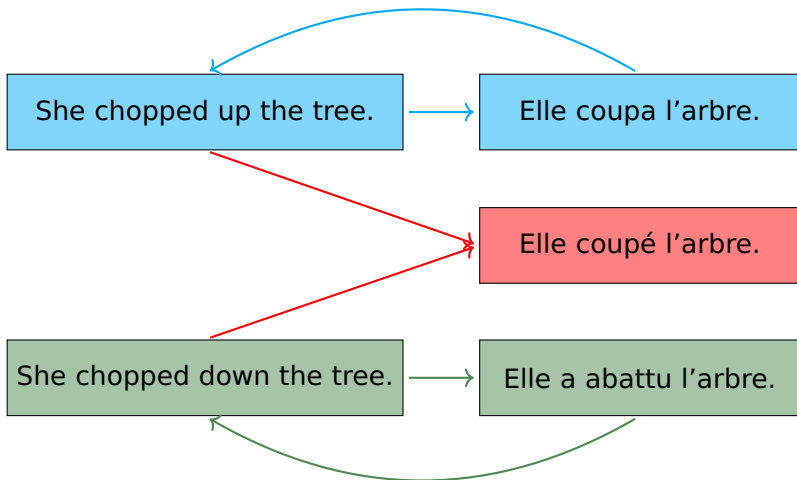
Cohn-Gordon and Goodman 2019

Machine translation




Cohn-Gordon and Goodman 2019

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Cohn-Gordon and Goodman 2019


Generating and following instructions


Behavior 

(a) **Base Speaker** *walk forward four times*

Rational Speaker *go forward four segments to the intersection with the bare concrete hall*

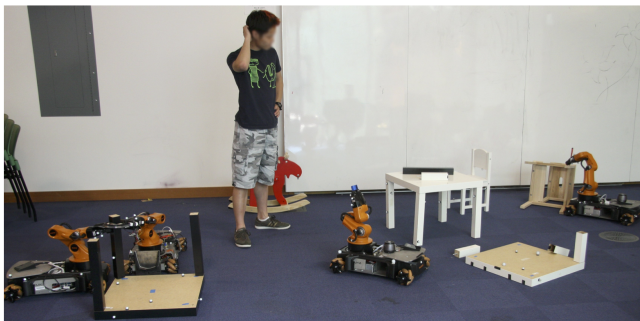
Instruction *walk along the blue carpet and you pass two objects*

(b) **Base Listener** 

Rational Listener 

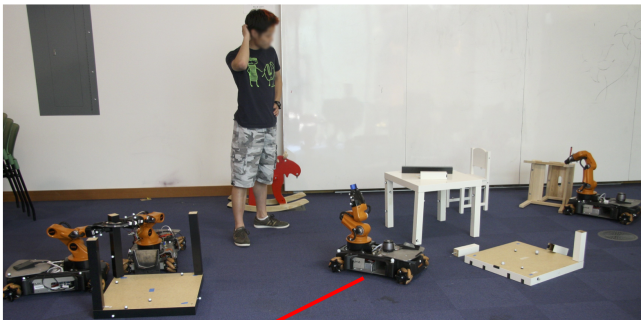
Fried et al. 2018

Collaborative problem solving



Tellex et al. 2014

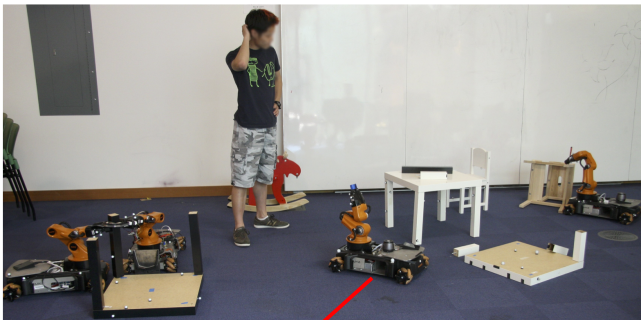
Collaborative problem solving



Help me!

Tellex et al. 2014

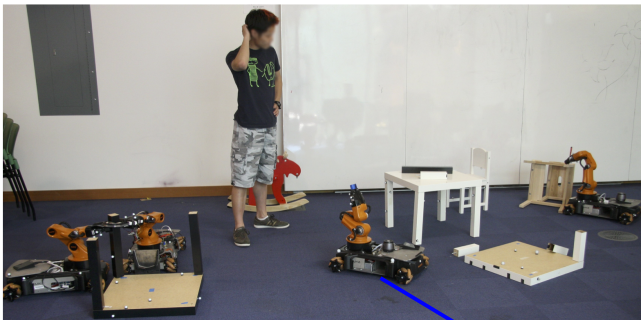
Collaborative problem solving



Hand me
the leg

Tellex et al. 2014

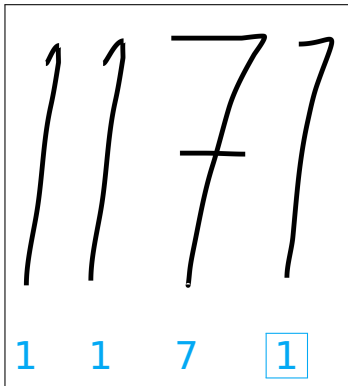
Collaborative problem solving



Hand me the white leg on the table

Tellex et al. 2014

Optical character recognition

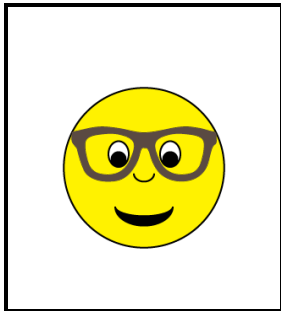


Conversational implicature

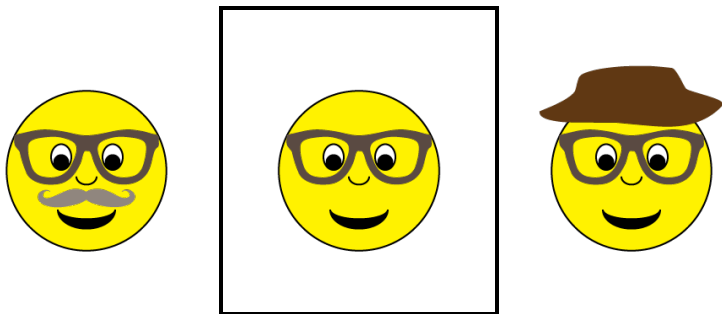
A particularized Quantity implicature



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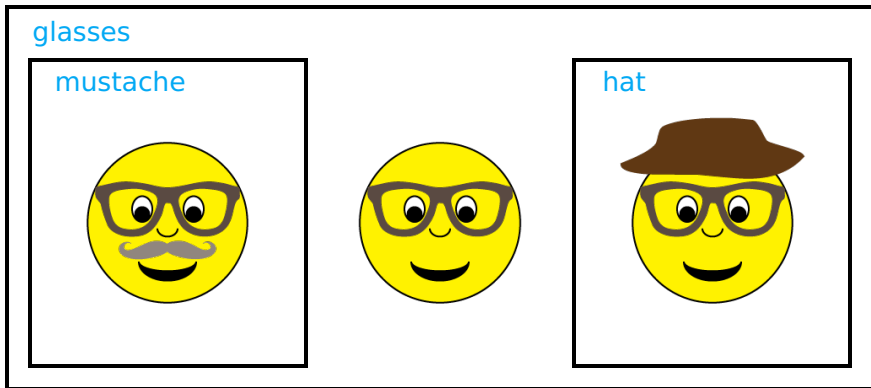


A particularized Quantity implicature



“The guy with glasses”

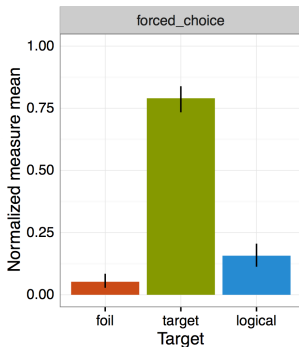
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“The guy with glasses”

Reference games

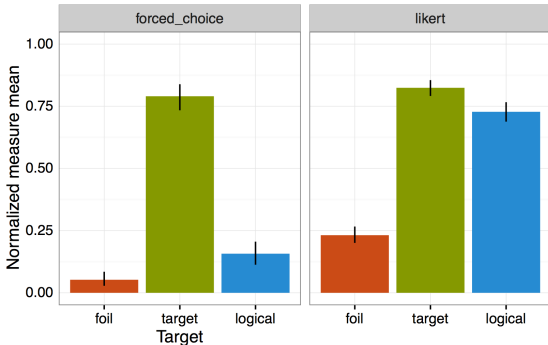
10 experiments, each $N \approx 600$ (4,651 participants). The summary picture:



Frank et al. 2016; <https://github.com/langcog/pragmods>

Reference games

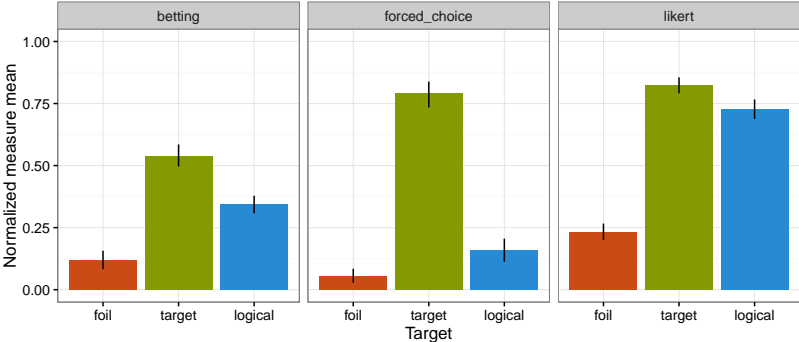
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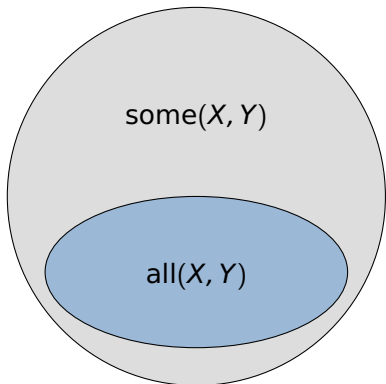
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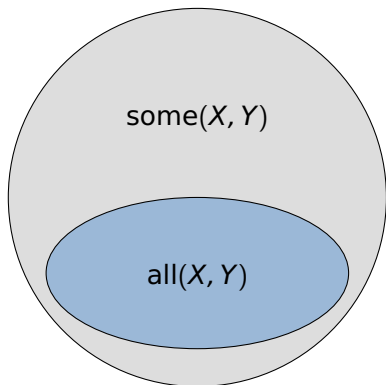
Scalar implicature

John Stuart Mill: *I saw **some** of your children to-day* invites the inference that I didn't see **all** of them



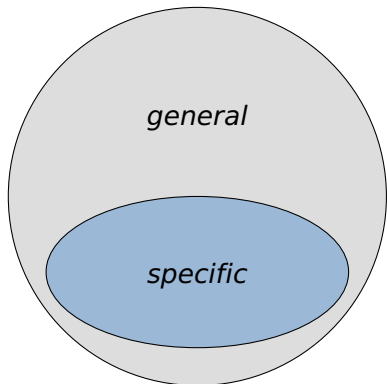
Scalar implicature

John Stuart Mill: *I saw **some** of your children to-day* invites the inference that I didn't see **all** of them "not because the words mean it, but because, if I had seen them all, it is most likely that I should have said so."



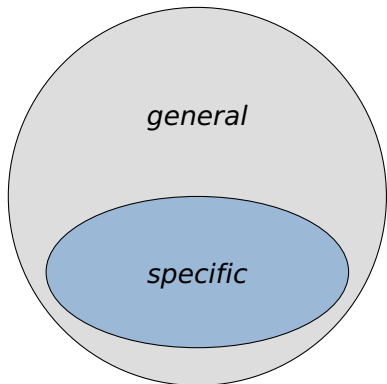
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Generalization: Using a general term invites the inference that its more specific, salient alternatives are inappropriate.



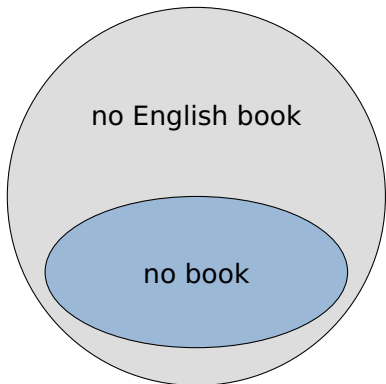
Scalar implicature

Generalization: Using a general term invites the inference that its **more specific, salient** alternatives are inappropriate.



Scalar implicature

Strawson and Grice: *there are no English books here* invites the inference that there are books here.

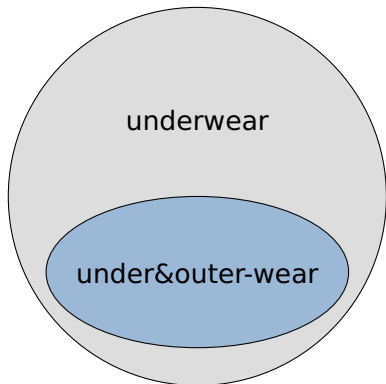


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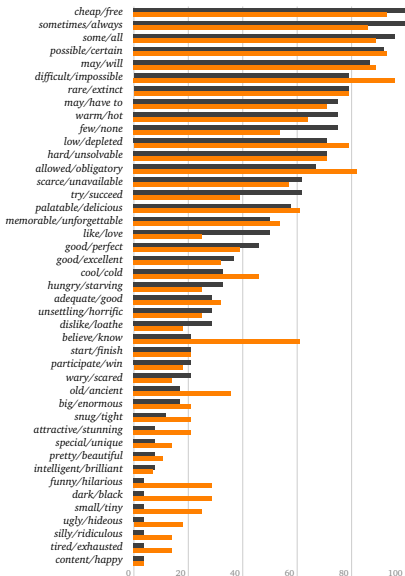
Chris Potts: Watching TV in your underwear – that’s a scalar implicature!

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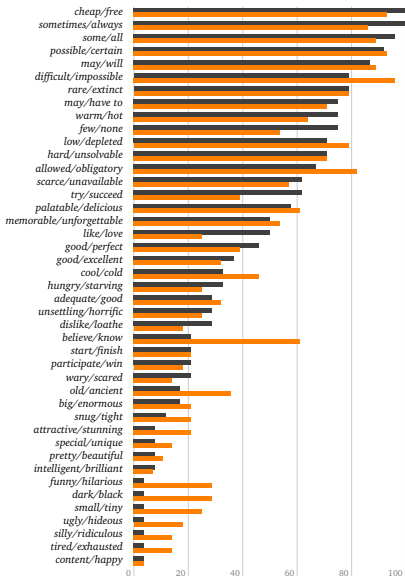


Scalar diversity



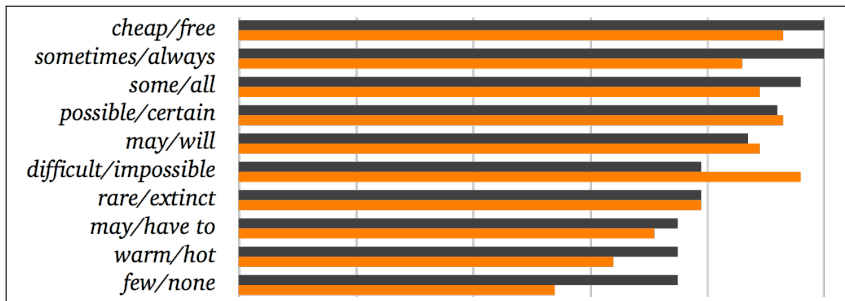
van Tiel et al. 2016;
see also Degen 2013

Scalar diversity



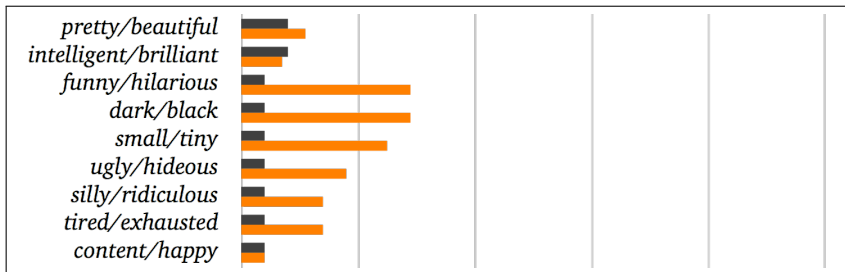
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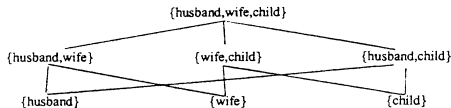
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Partial-order implicature

Hirschberg 1985

Partial-order implicature

- A:** Do you speak German?
- B:** My husband does.

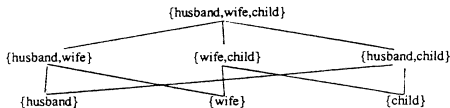


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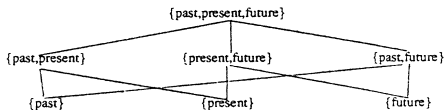
A: Do you speak German?

B: My husband does.



A: Are you on your honeymoon?

B: Well, I was.



Hirschberg 1985

I-implicature

Levinson (2000): “what is simply described is stereotypically exemplified”

I-implicature

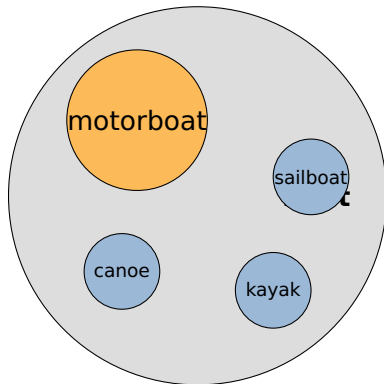
Levinson (2000): “what is simply described is stereotypically exemplified”

1. At a busy marina in water-skiing country:
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1. At a busy marina in water-skiing country:
“boat” interpreted as *motorboat*
2. Kim is in France. (in Paris)
3. I hit the button and it started. (causation)
4. Sandy finished the book. (reading)

The Rational Speech Acts model (RSA)

Origin story

Origin story

- **Rosenberg and Cohen (1964)**: early Bayesian model of production and comprehension

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- **Lewis (1969)**: signaling systems

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- **Frank and Goodman (2012)**: very sophisticated pragmatic agents and a new Bayesian foundation

Pragmatic listeners

Pragmatic listeners

Literal listener

$$L_{\text{lit}}(\textit{state} \mid \textit{msg}) = \frac{\llbracket \textit{msg}, \textit{state} \rrbracket P(\textit{state})}{\sum_{\textit{state}'} \llbracket \textit{msg}, \textit{state}' \rrbracket P(\textit{state}')}$$

Pragmatic listeners

Pragmatic speaker

$$S_{\text{prag}}(\text{msg} \mid \text{state}) = \frac{\exp(\alpha(\log L_{\text{lit}}(\text{state} \mid \text{msg}) - C(\text{msg})))}{\sum_{\text{msg}'} \exp(\alpha(\log L_{\text{lit}}(\text{state} \mid \text{msg}') - C(\text{msg}'))))$$

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Pragmatic listeners

Pragmatic listener

$$L_{\text{prag}}(\textit{state} \mid \textit{msg}) = \textbf{pragmatic speaker} \times \textit{state prior}$$

Pragmatic speaker

$$S_{\text{prag}}(\textit{msg} \mid \textit{state}) = \textbf{literal listener} - \textit{message costs}$$

Literal listener

$$L_{\text{lit}}(\textit{state} \mid \textit{msg}) = \textbf{lexicon} \times \textit{state prior}$$

A simple example



<i>beard</i>	1	0	0
<i>glasses</i>	1	1	0
<i>tie</i>	0	1	1

L_{prag}

S_{prag}

L_{lit}

$[\cdot]$

A simple example



<i>beard</i>	1	0	0
<i>glasses</i>	.5	.5	0
<i>tie</i>	0	.5	.5


L_{prag}

S_{prag}

L_{lit}

$[\cdot]$

A simple example

	<i>beard</i>	<i>glasses</i>	<i>tie</i>
	.67	.33	0
	0	.5	.5
	0	0	1

L_{prag}

S_{prag}

L_{lit}

$[\cdot]$

A simple example



<i>beard</i>	1	0	0
<i>glasses</i>	.40	.60	0
<i>tie</i>	0	.33	0.67

L_{prag}

S_{prag}

L_{lit}

$[\cdot]$

Pragmatic speakers

Pragmatic speakers

Literal speaker

$$S_{lit}(msg | state) = \frac{\exp(\alpha(\log\llbracket msg, state \rrbracket - C(msg)))}{\sum_{msg'} \exp(\alpha(\log\llbracket msg', state \rrbracket - C(msg')))}$$

Pragmatic speakers

Pragmatic listener

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Pragmatic listener

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Literal speaker

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Major achievements

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- **M-implicatures** (Bergen et al. 2016)

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Joint inference

$$L_{\text{prag}}(\textit{state}, \textit{Context} \mid \textit{msg})$$

$$S_{\text{prag}}(\textit{msg} \mid \textit{state}, \textit{Context})$$

RSA/ML hybrids

Motivation

Motivation

- Discriminative image labeling

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- Image captioning

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- Impact

A formative challenge

$$S_{\text{prag}}(\text{msg} \mid \text{state}) = \frac{\exp(\alpha(\log L_{\text{lit}}(\text{state} \mid \text{msg}) - C(\text{msg})))}{\sum_{\text{msg}'} \exp(\alpha(\log L_{\text{lit}}(\text{state} \mid \text{msg}') - C(\text{msg}'))))$$

Notational conventions

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Logical semantic agents

$$S_{\text{prag}}(\textit{msg} \mid \textit{state}; \textit{Context}, [\cdot])$$

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$$S_{\text{prag}}(\textit{msg} \mid \textit{state}; \textit{Context}, \llbracket \cdot \rrbracket)$$

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Notational conventions

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$$S_{\text{prag}}^{\llbracket \cdot \rrbracket}(\text{msg} \mid \text{state})$$

Learned agents

$$\mathbf{S}_{\text{prag}}(\text{msg} \mid \text{state}; \text{Context}, \theta)$$

Notational conventions

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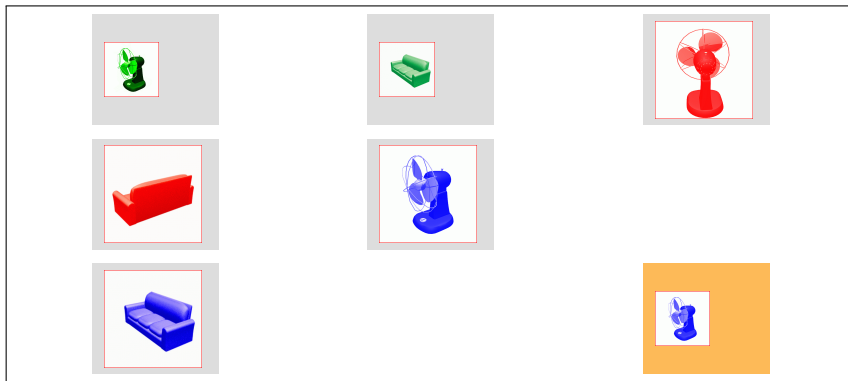
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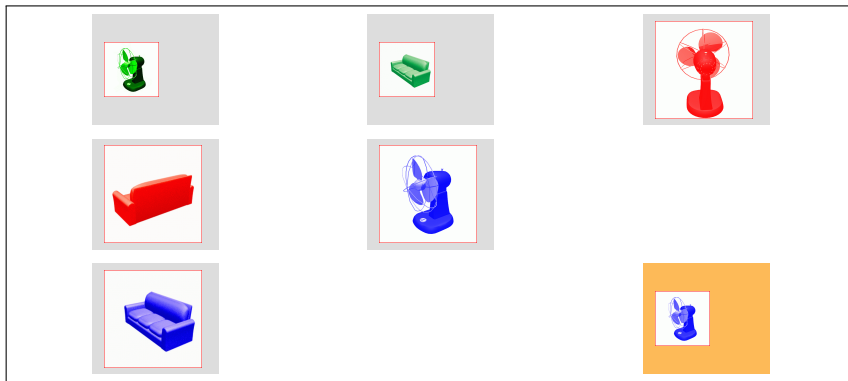
$$\mathbf{S}_{\text{prag}}^{\theta}(\text{msg} \mid \text{state})$$

RSA learning objectives

TUNA furniture example










TUNA furniture example



Utterance: “blue fan small”

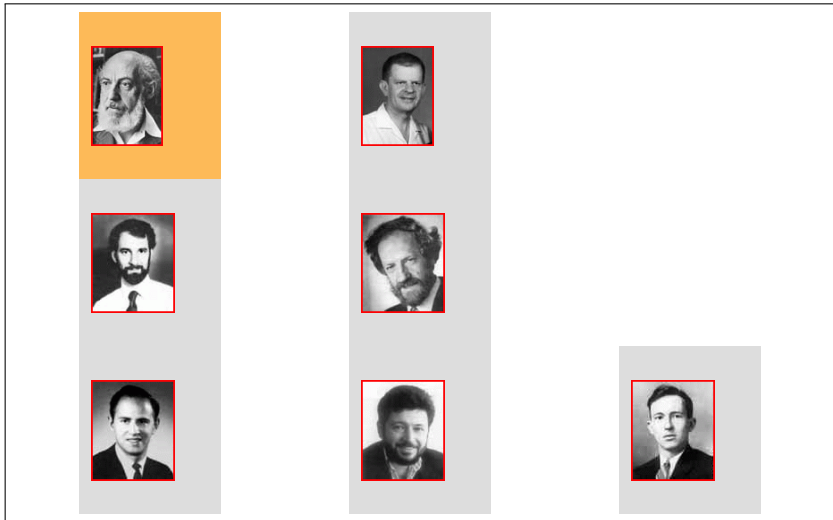
TUNA furniture example

 <p>colour:green orientation:left size:small type:fan x-dimension:1 y-dimension:1</p>	 <p>colour:green orientation:left size:small type:sofa x-dimension:1 y-dimension:2</p>	 <p>colour:red orientation:back size:large type:fan x-dimension:1 y-dimension:3</p>
 <p>colour:red orientation:back size:large type:sofa x-dimension:2 y-dimension:1</p>	 <p>colour:blue orientation:left size:large type:fan x-dimension:2 y-dimension:2</p>	
 <p>colour:blue orientation:left size:large type:sofa x-dimension:3 y-dimension:1</p>		 <p>colour:blue orientation:left size:small type:fan x-dimension:3 y-dimension:3</p>

Utterance: “blue fan small”

Utterance attributes: [*colour:blue*]; [*size:small*]; [*type:fan*]

TUNA people example










TUNA people example



Utterance: "The bald man with a beard"

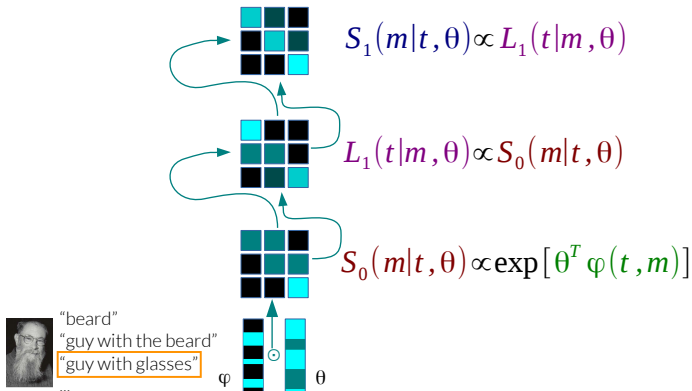
TUNA people example

 <p>age:old hairColour:light hasBeard:1 hasGlasses:0 hasHair:0 hasShirt:1 hasSuit:0 hasTie:0 type:person</p>	 <p>age:young hairColour:dark hasBeard:0 hasGlasses:0 hasHair:1 hasShirt:1 hasSuit:0 hasTie:0 type:person</p>	
 <p>age:young hairColour:dark hasBeard:1 hasGlasses:0 hasHair:1 hasShirt:1 hasSuit:0 hasTie:1 type:person</p>	 <p>age:young hairColour:dark hasBeard:1 hasGlasses:0 hasHair:1 hasShirt:0 hasSuit:1 hasTie:1 type:person</p>	
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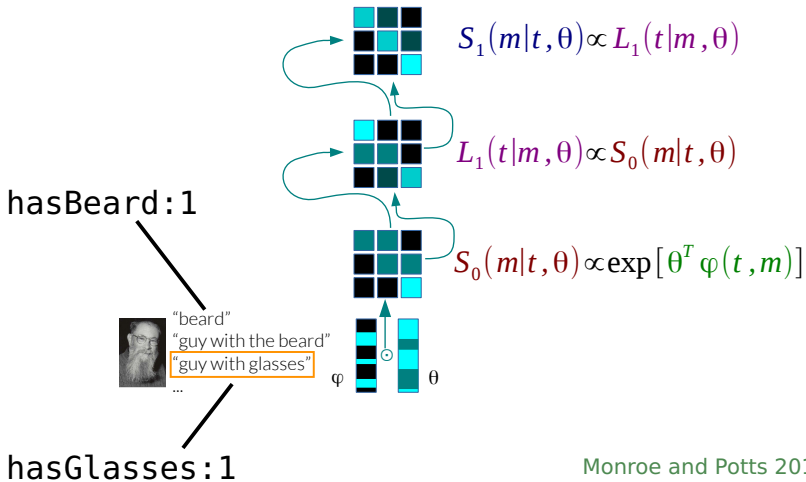
Utterance attributes: [*hasBeard:1*]; [*hasHair:0*]; [*type:person*]

Forward inference



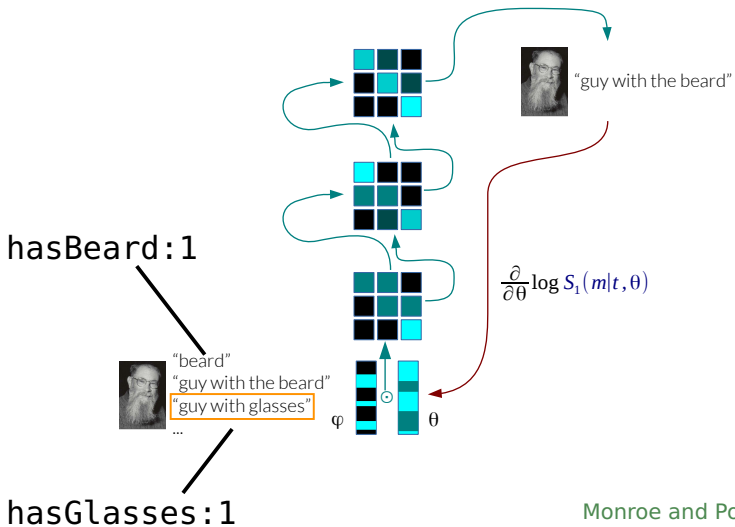
Monroe and Potts 2015

Forward inference



Monroe and Potts 2015

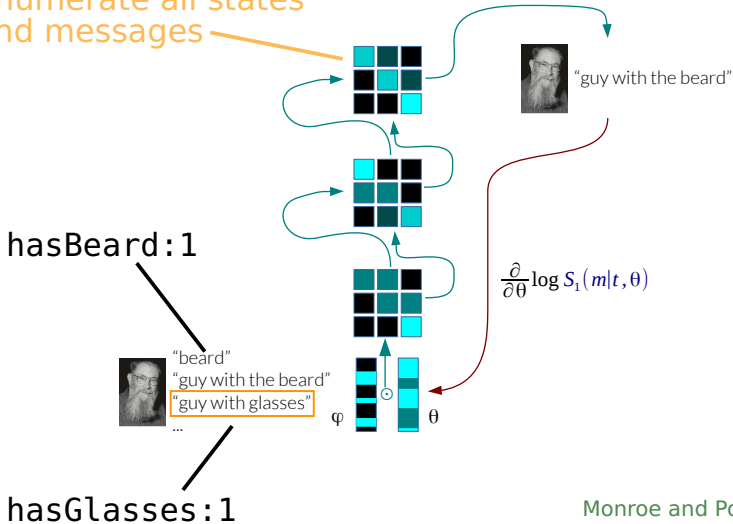
Optimization



Monroe and Potts 2015

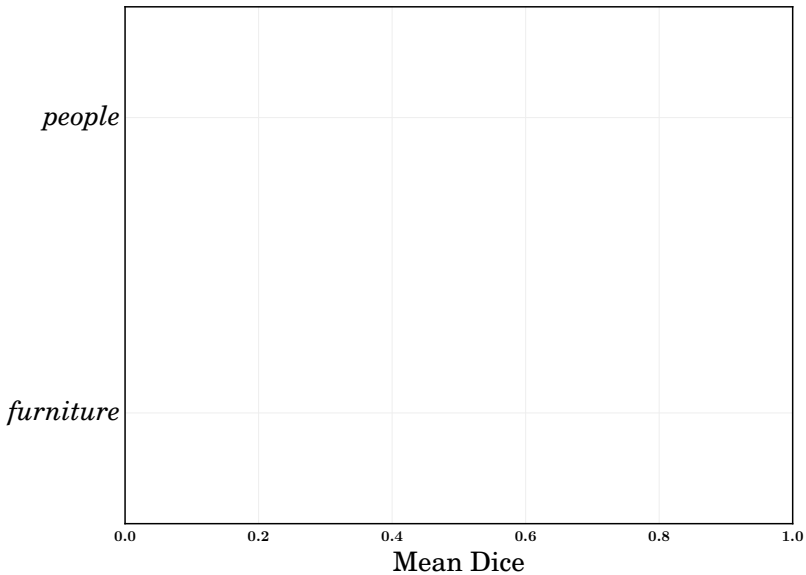
Optimization

Enumerate all states and messages

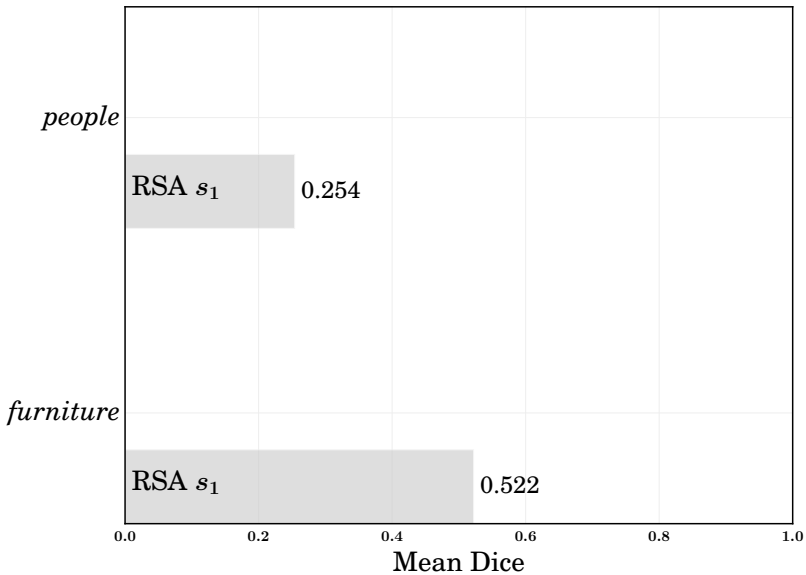


Monroe and Potts 2015

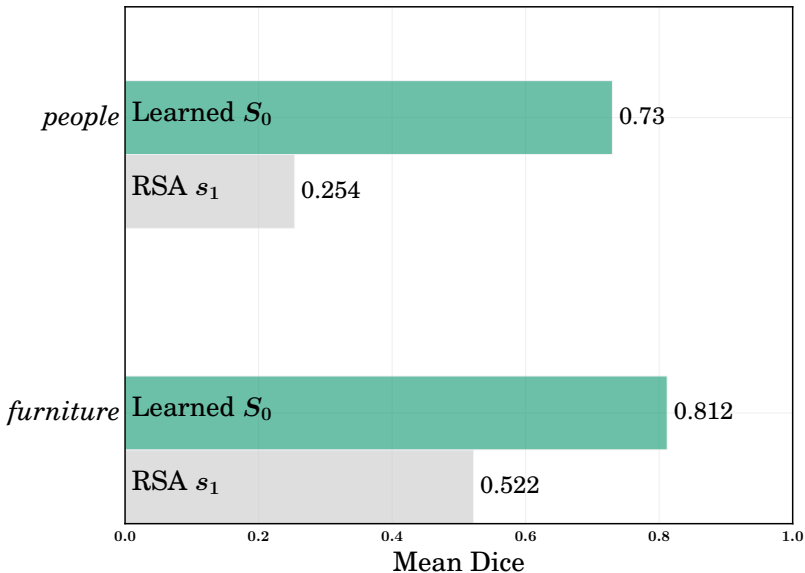
TUNA Results



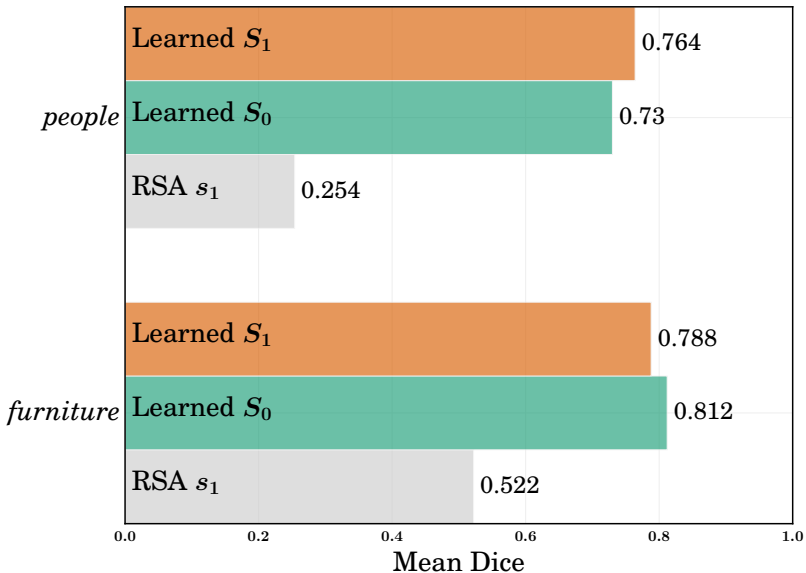
TUNA Results



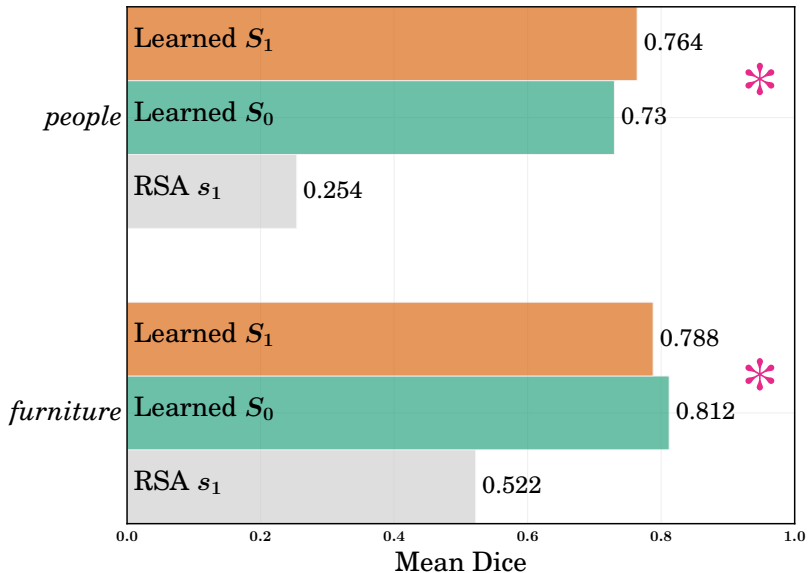
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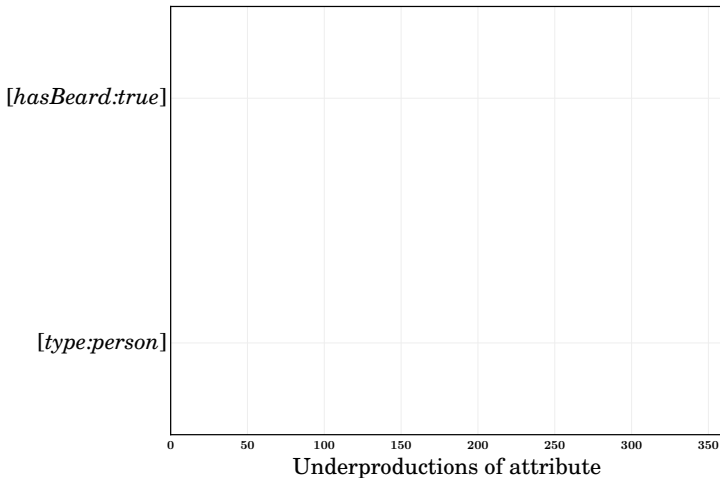
TUNA Results



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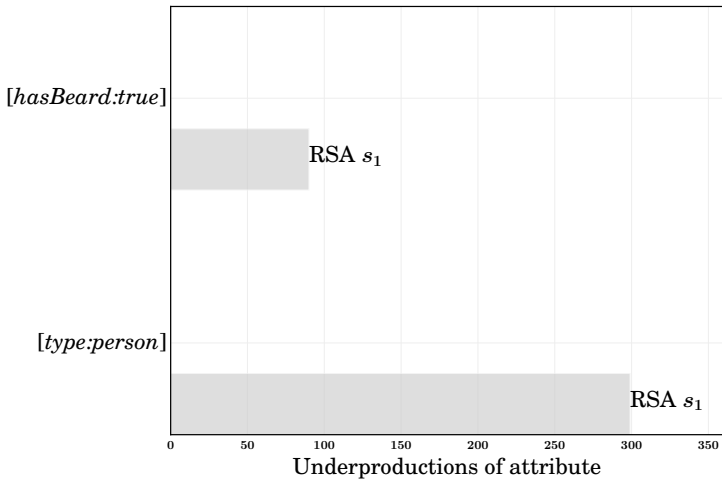


Error analysis



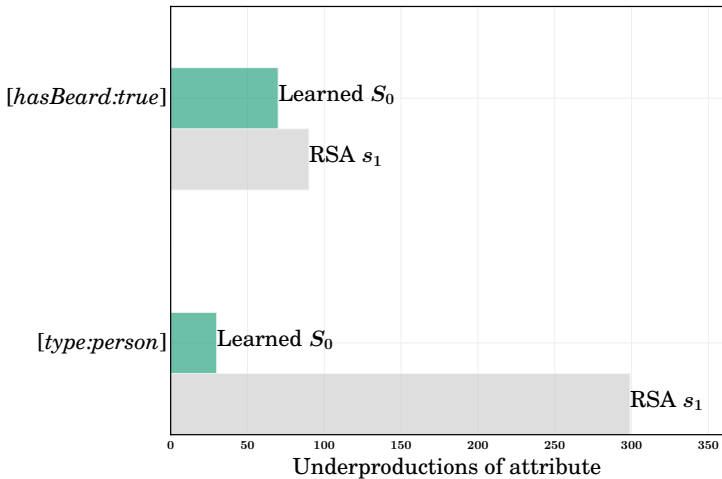
(Lower is better!)

Error analysis



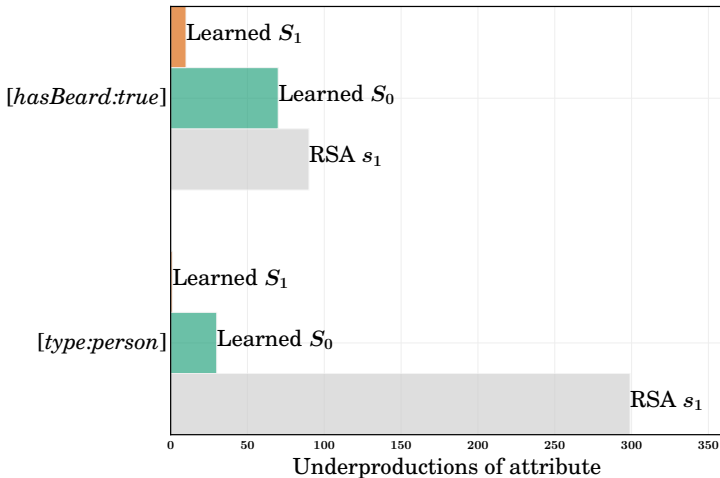
(Lower is better!)

Error analysis



(Lower is better!)

Error analysis



(Lower is better!)

Limitations

- Scalability
- Sensitivity to variation
- Bounded rationality
- New kinds of model assessment
- Impact



Introspective speakers from Google

Generation and Comprehension of Unambiguous Object Descriptions

Junhua Mao^{2*} Jonathan Huang¹ Alexander Toshev¹ Oana Camburu³ Alan Yuille^{2,4} Kevin Murphy¹
¹Google Inc. ²University of California, Los Angeles ³University of Oxford ⁴Johns Hopkins University
{mjhustc@, yuille@stat.}ucla.edu, oana-maria.camburu@cs.ox.ac.uk
{jonathanhuang, toshev, kpmurphy}@google.com

Context-aware Captions from Context-agnostic Supervision

Ramakrishna Vedantam¹ Samy Bengio² Kevin Murphy² Devi Parikh³ Gal Chechik²
¹Virginia Tech ³Georgia Institute of Technology ²Google
¹vrama91@vt.edu ³parikh@gatech.edu ²{bengio, kpmurphy, gal}@google.com

Mao et al. 2016; Vedantam et al. 2017

Google Refexp Dataset



Mao et al. 2016

Google Refexp Dataset



Mao et al. 2016

Google Refexp Dataset



S: "A backpack"

Mao et al. 2016

Google Refexp Dataset



S: "A backpack"

Listener

Mao et al. 2016

Google Refexp Dataset



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Listener

Mao et al. 2016

Google Refexp Dataset



Mao et al. 2016

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S: "A yellow and black backpack"

Mao et al. 2016

Google Refexp Dataset



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Listener

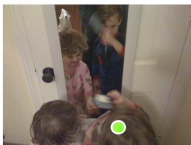
Google Refexp Dataset



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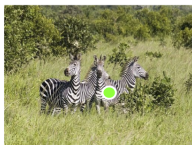
Listener

Google Refexp Dataset examples



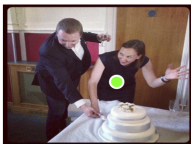
A boy brushing his hair while looking at his reflection.

A young male child in pajamas shaking around a hairbrush in the mirror.



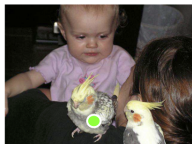
Zebra looking towards the camera.

A zebra third from the left.



The woman in black dress.

A lady in a black dress cuts a wedding cake with her new husband.



A bird that is close to the baby in a pink shirt.

A bird standing on the shoulder of a person with its tail touching her face.

Introspective speaker training

$$\Delta(I, state, state') = \operatorname{argmax}_{msg} \left[\lambda \log \mathbf{s}_{lit}^{\theta}(msg | state; I_n) + (1 - \lambda) \log \frac{\mathbf{s}_{lit}^{\theta}(msg | state; I_n)}{\mathbf{s}_{lit}^{\theta}(msg | state'; I_n)} \right]$$

Proportional to a standard RSA \mathbf{L}_1 .

Diagnosing the role of introspection

Target image and class

Rufous Hummingbird



Justifications vary with λ

fully
discriminative

- $\lambda = 0.00$ tarsals orange white brown wings wings orange tail dark an primaries
- $\lambda = 0.30$ This is a brown bird with a brown wing and a long pointy beak.
- $\lambda = 0.50$ This bird is **brown with red on its neck** and has a long , pointy beak.
- $\lambda = 0.70$ This is a bird with a **white belly , brown wing and a red throat.**
- $\lambda = 1.00$ A small sized bird that has a very long and pointed bill.

context blind

Distractor class

Ruby throated Hummingbird



Vedantam et al. 2017

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Vedantam et al. 2017

Modular neural RSA

Papers employing these general techniques

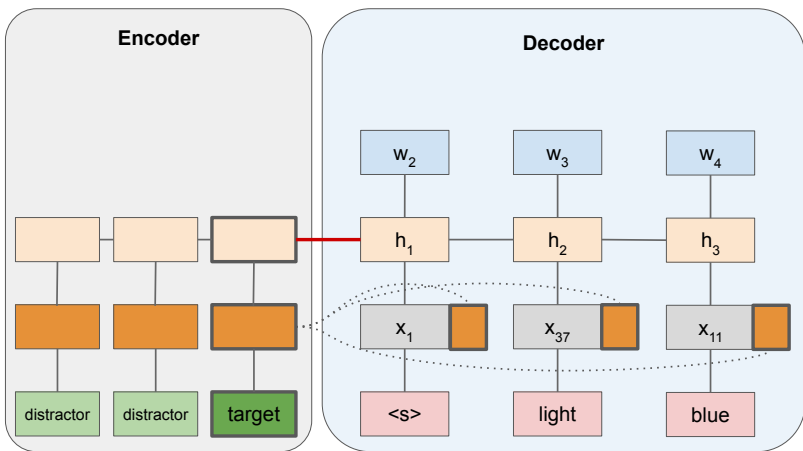
- Andreas and Klein. 2016. Reasoning about pragmatics with neural listeners and speakers. *EMNLP*.
- Fried, Andreas, Klein. 2018. Unified pragmatic models for generating and following instructions. *NAACL*.
- Monroe, Hawkins, Goodman, Potts. Colors in context: A pragmatic neural model for grounded language understanding. *TACL*.
- Monroe, Hu, Jong, Potts. 2018. Generating bilingual pragmatic color references. *NAACL*.

Stanford English Colors in Context corpus

	Context		Utterance
			blue
			The darker blue one
			dull pink not the super bright one
			Purple
			blue

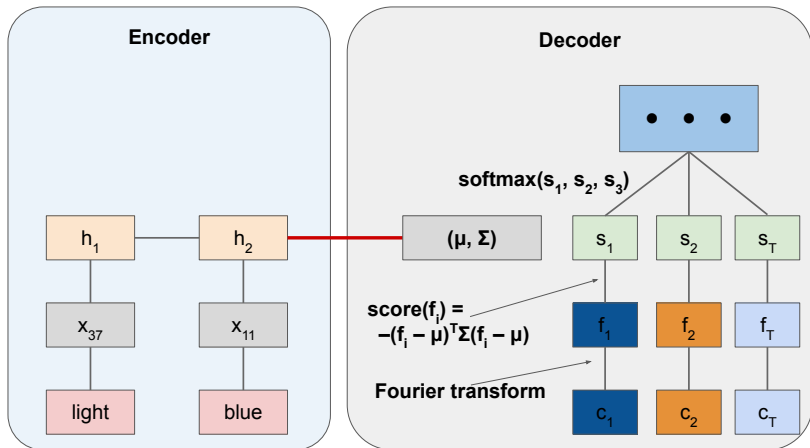
Stanford Colors in Context corpus (Monroe et al. 2017).
Chinese version available as well (Monroe et al. 2018)!

Literal neural speaker S_{lit}^θ



Monroe et al. 2017

Neural literal listener L_0



Monroe et al. 2017

The formative challenge again

$$S_{\text{prag}}(\text{msg} \mid \text{state}) = \frac{\exp(\alpha(\log L_{\text{lit}}(\text{state} \mid \text{msg}) - C(\text{msg})))}{\sum_{\text{msg}'} \exp(\alpha(\log L_{\text{lit}}(\text{state} \mid \text{msg}') - C(\text{msg}'))))$$

Neural pragmatic agents

Neural pragmatic agents

Neural pragmatic speaker (Andreas and Klein 2016)

$$s_{\text{prag}}^{\theta}(msg | state) = \frac{L_0(state | msg)}{\sum_{msg' \in X} L_0(state | msg')}$$

with X a sample from $s_{\text{lit}}^{\theta}(msg | state)$ such that $msg \in X$.

Neural pragmatic agents

Neural pragmatic speaker (Andreas and Klein 2016)

$$\mathbf{s}_{\text{prag}}^{\theta}(msg | state) = \frac{\mathbf{L}_0(state | msg)}{\sum_{msg' \in X} \mathbf{L}_0(state | msg')}$$

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Neural pragmatic listener

$$\mathbf{L}_1(state | msg) \propto \mathbf{s}_{\text{prag}}^{\theta}(msg | state)$$

Neural pragmatic agents

Neural pragmatic speaker (Andreas and Klein 2016)

$$s_{\text{prag}}^{\theta}(msg | state) = \frac{L_0(state | msg)}{\sum_{msg' \in X} L_0(state | msg')}$$

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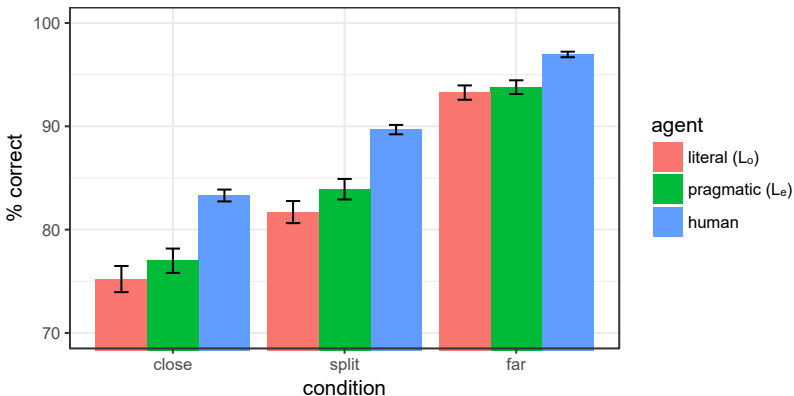
Neural pragmatic listener

$$L_1(state | msg) \propto s_{\text{prag}}^{\theta}(msg | state)$$

Blended neural pragmatic listener

Weighted combination of L_0 and L_1 .

English Colors in Context results



Monroe et al. 2017

Incremental pragmatics

The speaker normalization challenge again

$$S_{\text{prag}}(\text{msg} \mid \text{state}) = \frac{\exp(\alpha(\log L_{\text{lit}}(\text{state} \mid \text{msg}) - C(\text{msg})))}{\sum_{\text{msg}'} \exp(\alpha(\log L_{\text{lit}}(\text{state} \mid \text{msg}') - C(\text{msg}'))))$$

The speaker normalization challenge again

$$S_{\text{prag}}(\text{msg} | \text{state}) = \frac{\exp(\alpha(\log L_{\text{lit}}(\text{state} | \text{msg}) - C(\text{msg})))}{\sum_{\text{msg}'} \exp(\alpha(\log L_{\text{lit}}(\text{state} | \text{msg}') - C(\text{msg}'))))$$

Sampling

$$\mathbf{s}_{\text{prag}}^{\theta}(\text{msg} | \text{state}) = \frac{\mathbf{L}_0(\text{state} | \text{msg})}{\sum_{\text{msg}' \in X} \mathbf{L}_0(\text{state} | \text{msg}')}$$

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The speaker normalization challenge again

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Sampling

$$\mathbf{s}_{\text{prag}}^{\theta}(\text{msg} \mid \text{state}) = \frac{\mathbf{L}_0(\text{state} \mid \text{msg})}{\sum_{\text{msg}' \in X} \mathbf{L}_0(\text{state} \mid \text{msg}')}$$

with X a sample from $\mathbf{s}_{\text{lit}}^{\theta}(\text{msg} \mid \text{state})$ such that $\text{msg} \in X$.

Cohn-Gordon et al. (2018)

Not good enough!

The incremental RSA model

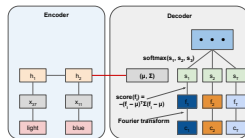
$$L_0^{\text{WORD}}(\text{state} \mid [\text{word}_1 \dots \text{word}_n], \text{word})$$

Cohn-Gordon et al. 2018, 2019

The incremental RSA model



$$L_0^{\text{WORD}}(\text{state} \mid [\text{word}_1 \dots \text{word}_n], \text{word})$$

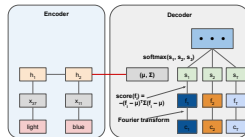


Cohn-Gordon et al. 2018, 2019

The incremental RSA model



$$L_0^{\text{WORD}}(\text{state} \mid [\text{word}_1 \dots \text{word}_n], \text{word})$$



$$S_1^{\text{WORD}}(\text{word} \mid [\text{word}_1 \dots \text{word}_n], \text{state}) =$$

$$\frac{L_0^{\text{WORD}}(\text{state} \mid [\text{word}_1 \dots \text{word}_n], \text{word})}{\sum_{\text{word}' \in \mathbf{V}} L_0^{\text{WORD}}(\text{state} \mid [\text{word}_1 \dots \text{word}_n], \text{word}')}$$

Evaluation

Using a separately trained S_0 , apply Bayes Rule to create a simple classifier (see also Newman et al. 2020). Each context contains the target and 9 distractors.

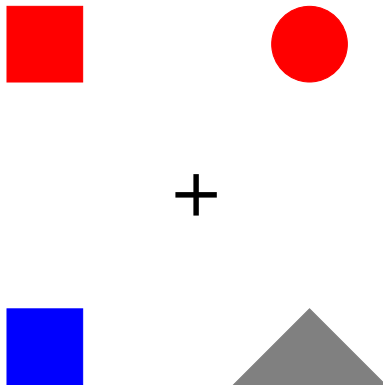
Visual Genome		
Model	Common objects	Confusable objects
Char S_0	48.9	47.5
Char S_1	68.0	65.9
Word S_0	57.6	53.4
Word S_1	60.6	57.6

Cohn-Gordon et al. 2018

Papers employing these general techniques

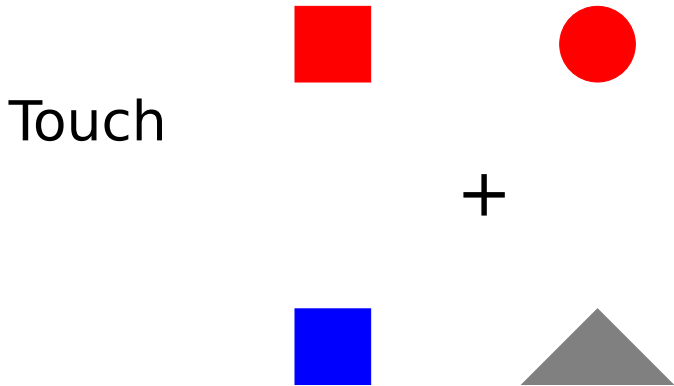
- Cohn-Gordon and Goodman. 2019. Lost in machine translation: a method to reduce meaning loss. *NAACL*.
- Cohn-Gordon, Goodman, Potts. 2018. Pragmatically informative image captioning with character-level inference. *SCiL*.
- Cohn-Gordon, Goodman, Potts. 2019. An incremental iterated response model of pragmatics. *SCiL*.
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Linguistic evidence for incremental pragmatics



Sedivy et al. 1999; Sedivy 2007; Grodner and Sedivy 2008

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Linguistic evidence for incremental pragmatics

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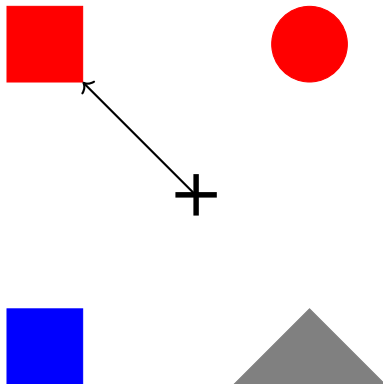
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Conclusions

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Thanks!

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