# Pragmatic description generation with cooperative networks

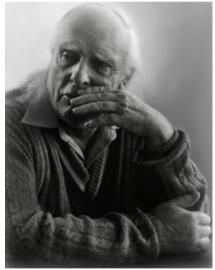
### Will Monroe CS224U / LINGUIST 188/288 18 May 2016

Work is work.

Examples adapted from Grice (1970)

Will produced a series of sounds that corresponded closely to the tune of "Hey Jude."

- "Make your contribution as informative as required [...]
- Do not make your contribution more informative than is required. [...]
- Do not say what you believe to be false. [...]
- Avoid obscurity of expression.
- Avoid ambiguity.
- Be brief (avoid unnecessary prolixity)."



#### (Grice, 1970)

Work is work.

"Make your contribution as informative as required"

Will produced a series of sounds that corresponded closely to the tune of "Hey Jude."

"Be brief (avoid unnecessary prolixity)."

How do you like my new haircut?





...It's shorter in the back!

"Be relevant."

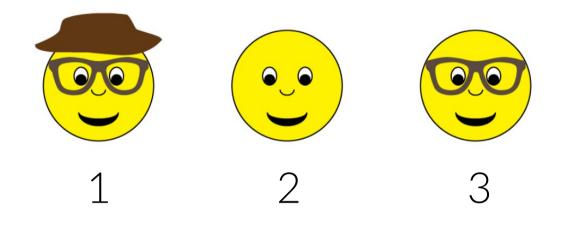
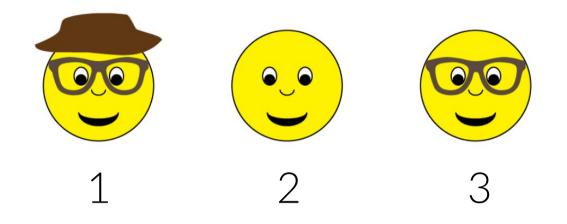
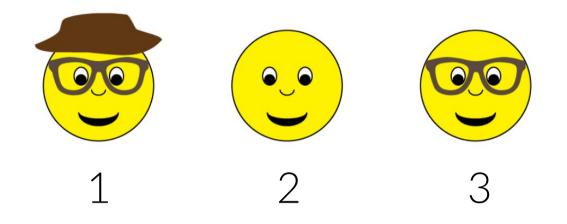


Image credit: Chris Potts



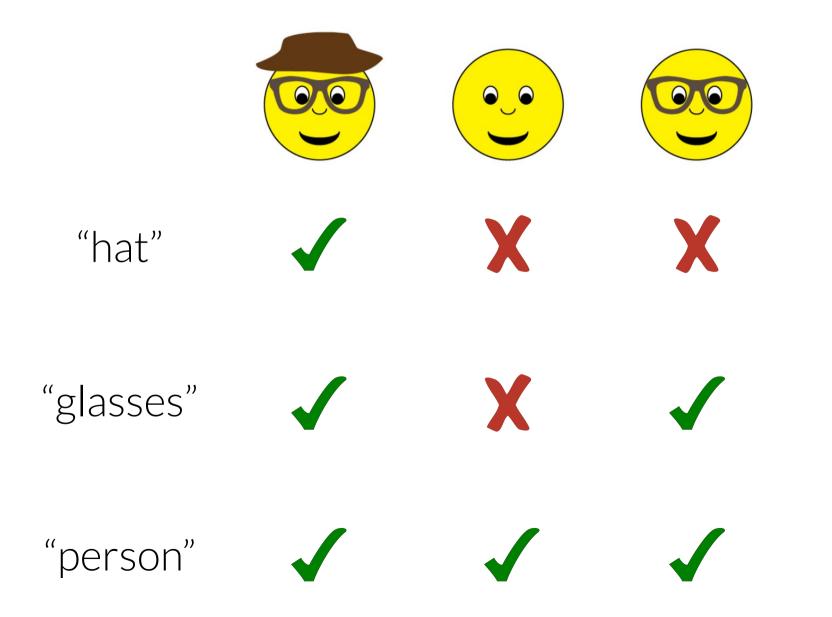
"glasses"

Image credit: Chris Potts



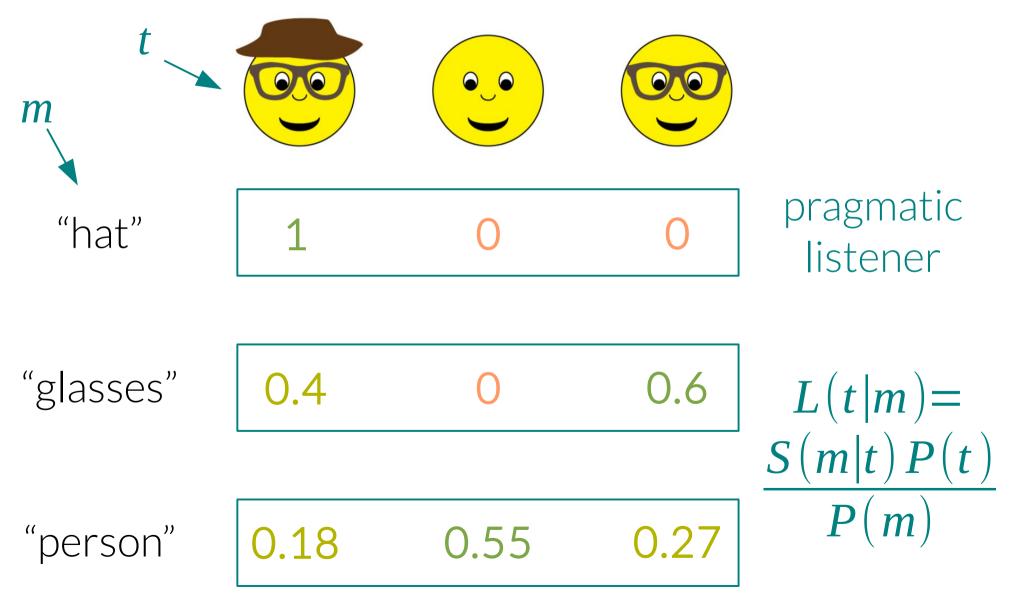
#### "person"

Image credit: Chris Potts









<sup>(</sup>Frank and Goodman, 2012)

## Recent RSA conquests

- marked verbosity
   "Will produced a series of sounds..."
   "Clark got the car to stop."
- ignorance implicature

   A: "Does Barb live in Moscow?"
   B: "She lives in Russia..."

• metaphor

"She's such a princess."

hyperbole

"a seven-million-dollar cup of coffee"

lexical uncertainty (Smith et al. 2013; Bergen et al. 2014)

question under discussion (Kao et al. 2014a/b)

## Two obstacles

1. Hand-written semantics

 $S \rightarrow C, S \rightarrow \neg C$  $C \rightarrow mLs, C \rightarrow m, C \rightarrow s$  $L \rightarrow \lor, L \rightarrow \land$ 

 $[m] = \{ \{Mary\}, \{Mary, Sue\} \}$  $[s] = \{ \{ Sue \}, \{ Mary, Sue \} \}$ 

[one] [ two ]  $= \{3\}$ [ three ] one or two two or three one or three one or two or three

 $=\{1,2,3\}$  $= \{2,3\}$ ={1,2,3}  $= \{2,3\}$  $=\{1,2,3\}$ ={1,2,3}

Can we learn from examples?

## Attribute Selection for REG









glasses

*¬tie* 

## Attribute Selection for REG

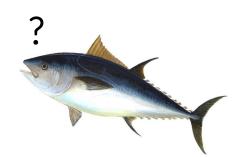




person beard glasses ¬tie person, beard person, glasses person, ¬tie glasses, beard

...

()



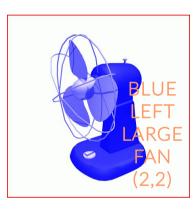
## The TUNA Corpus

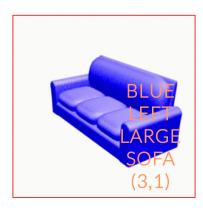


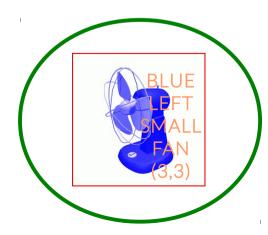








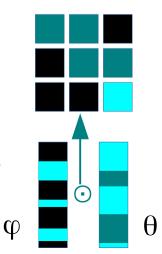




Human utterance: "**blue fan small**"

### Attributes: *blue*, *fan*, *small*

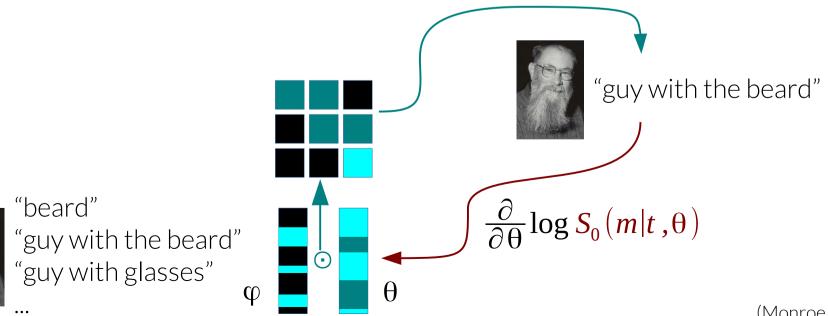
(van Deemter et al., 2006; Gatt et al., 2007)



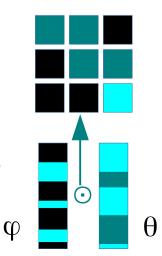
## $S_0(m|t,\theta) \propto \exp[\theta^T \varphi(t,m)]$

(Monroe and Potts, 2015)

"beard" "guy with the beard" "guy with glasses"



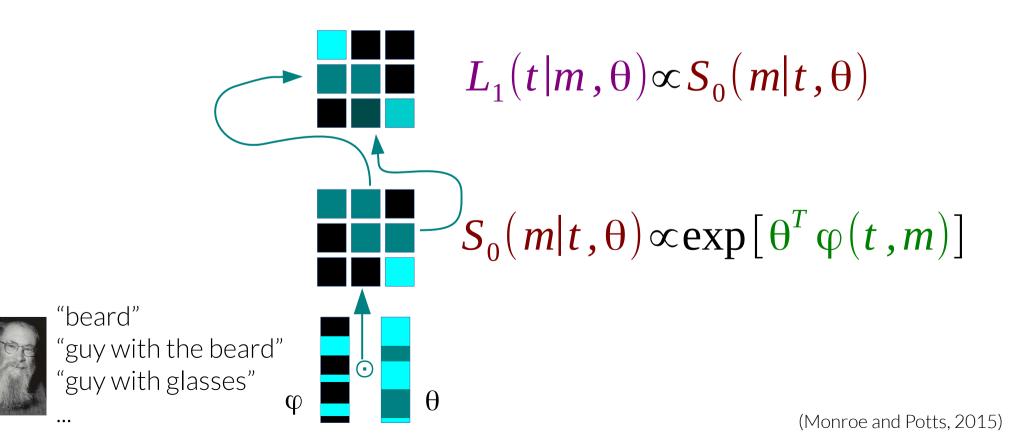
(Monroe and Potts, 2015)

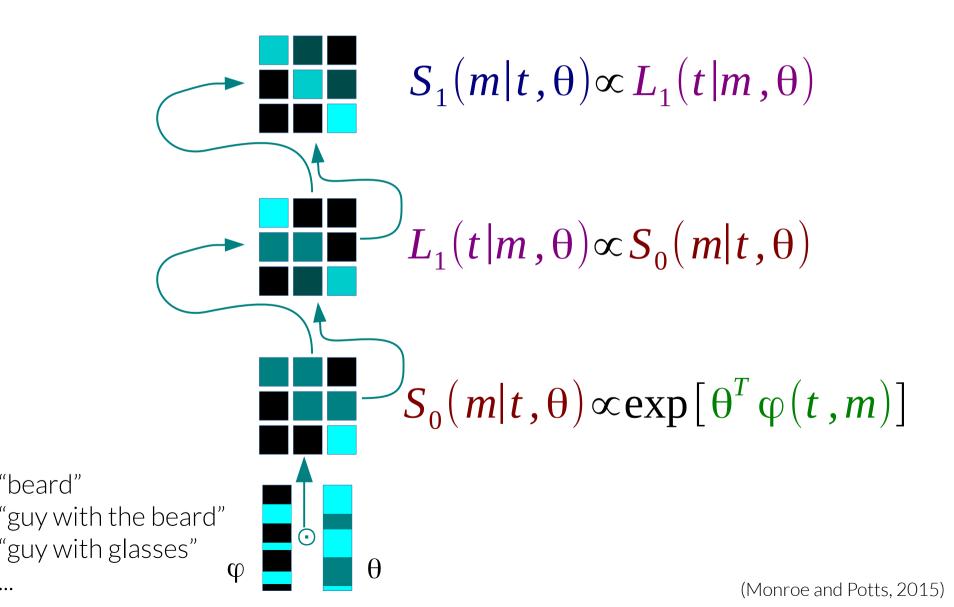


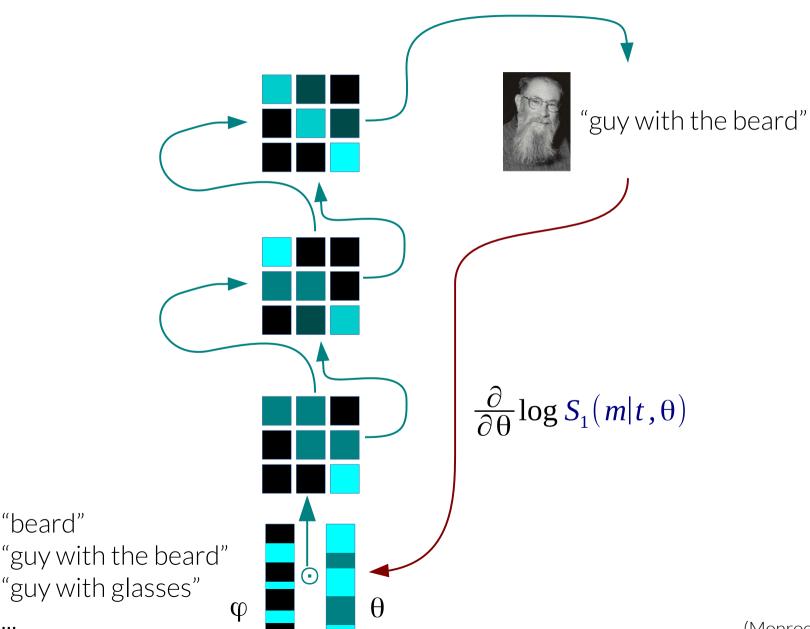
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...

(Monroe and Potts, 2015)





Avoid hand-built lexicon

Learn human quirks

Learn human quirks >> generation features

Avoid hand-built lexicon ≻ cross-product
BLUE → blue, BLUE → fan, ...

Learn human quirks > generation features

Avoid hand-built lexicon Learn human quirks

 people overproduce colors > generation features
 attribute type
 {color}

Avoid hand-built lexicon

Learn human quirks

- people overproduce colors
- attributes fit into a hierarchy

> generation features attribute type {color}

attribute pairs (pos/neg)
 {type}+{color}, {color}+¬{size}

Avoid hand-built lexicon

Learn human quirks

- people overproduce colors
- attributes fit into a hierarchy
- certain utterance lengths are preferred

generation features
 attribute type
 {color}

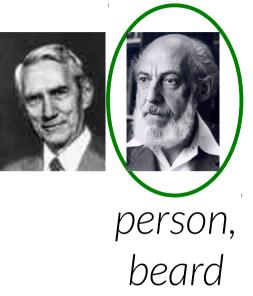
attribute pairs (pos/neg)
{type}+{color}, {color}+¬{size}
message size
{2 attrs}, {3 attrs}, ...

## Example: dataset

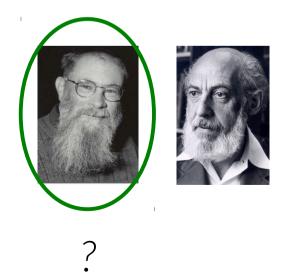
train



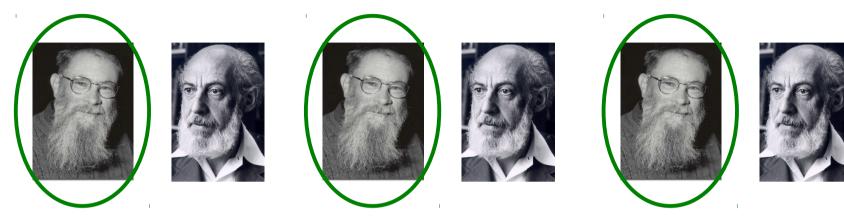
person, glasses



test



## Example: distributions



()

person glasses beard person, glasses person, beard glasses, beard all

Ø

RSA

## Example: distributions





.25



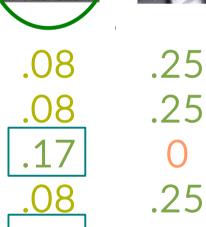












RSA

person glasses beard .08 person, glasses person, beard .08 glasses, beard .17 all .17

Ø







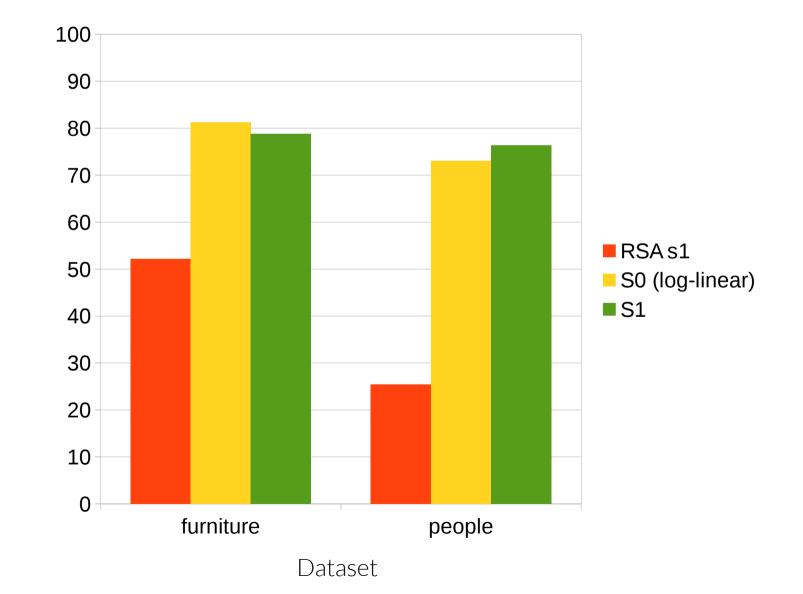
## Example: distributions



#### Example: distributions Ø .08 .25 .03 .00 .11 .10 .25 .22 .10 .13 .08 16 person glasses .03 .00 .07 beard .08 .25 .04 .17 78 73 person, glasses .01 .08 .18 person, beard .08 .25 .74 .12 .19 glasses, beard .00 .10 .17 .03 .11 all .17 .10 .22 .16 .11 RSA

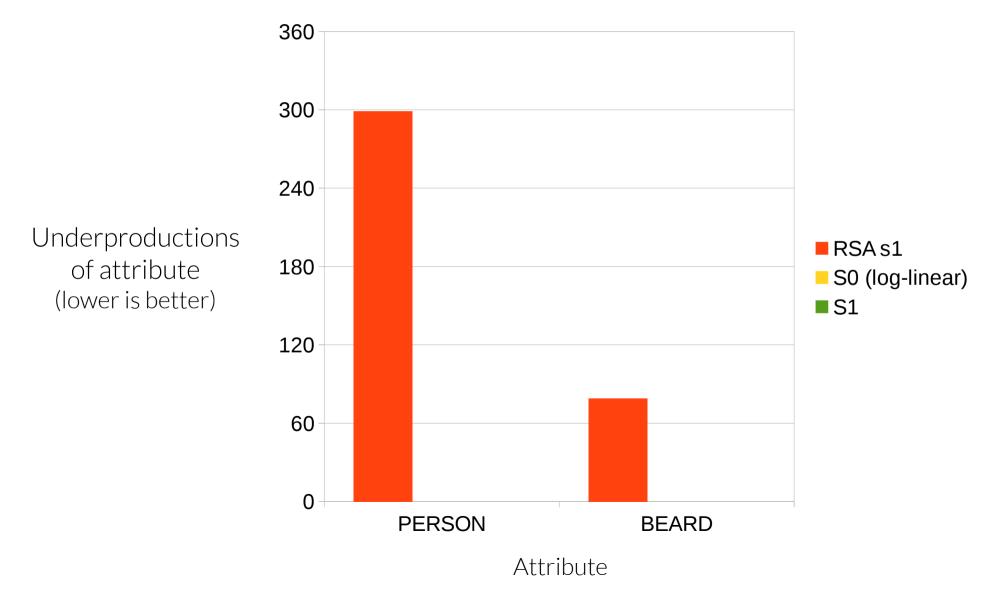
#### Example: distributions Ø .08 .25 .03 .00 .11 .10 .25 .22 .10 .13 .08 16 person glasses .03 .00 .07 beard .08 .25 .04 .17 78 73 person, glasses .01 .08 18 person, beard .08 .25 .74 .19 12 glasses, beard .00 .17 .03 .10 .11 all .17 .10 .16 .22 .11 RSA

### Experimental results

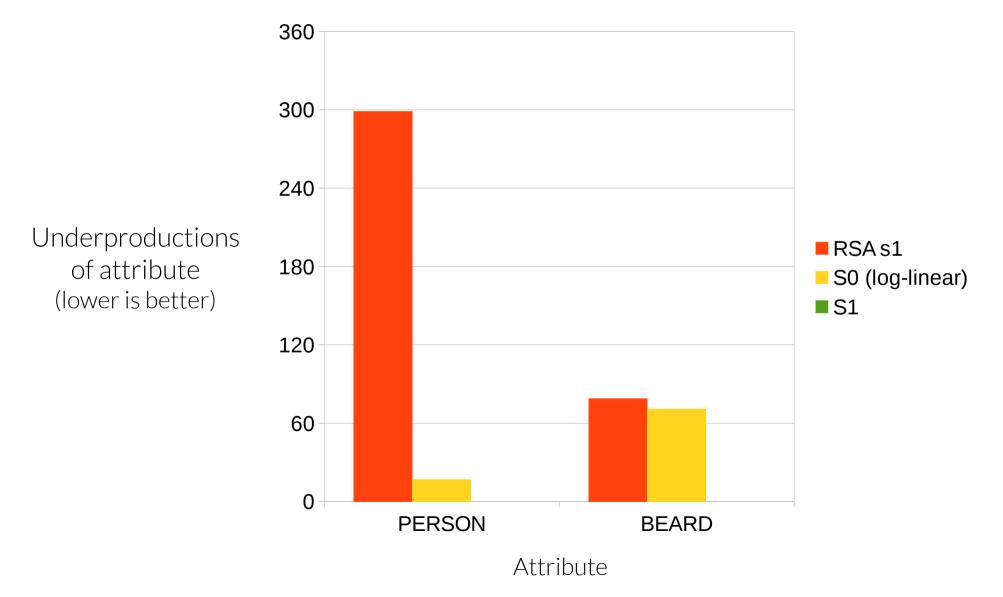


Dice (mean)

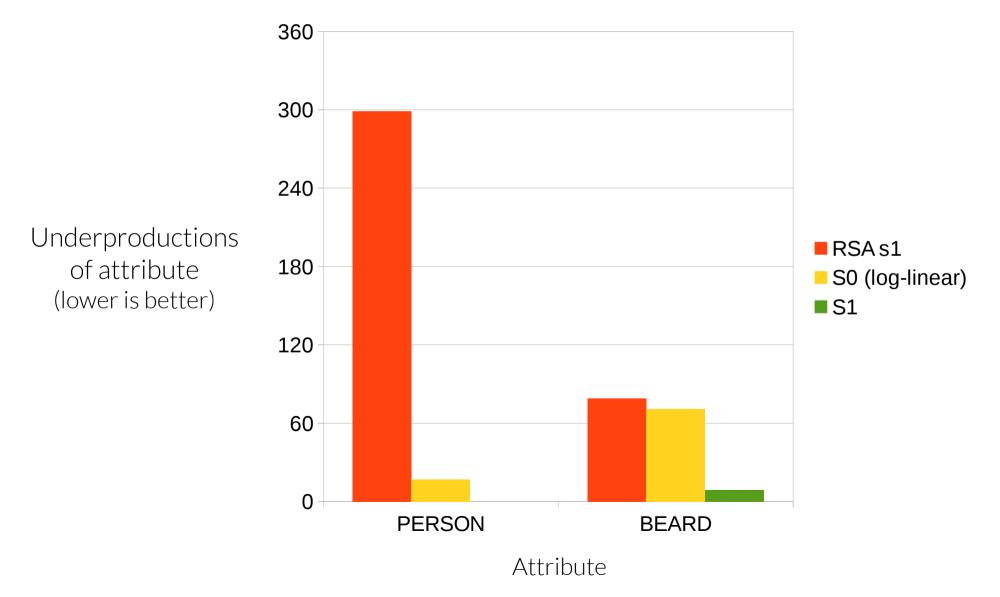
### Analysis TUNA *people* dataset



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### Analysis TUNA *people* dataset



### Two obstacles

1. Hand-written semantics

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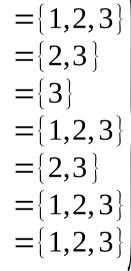
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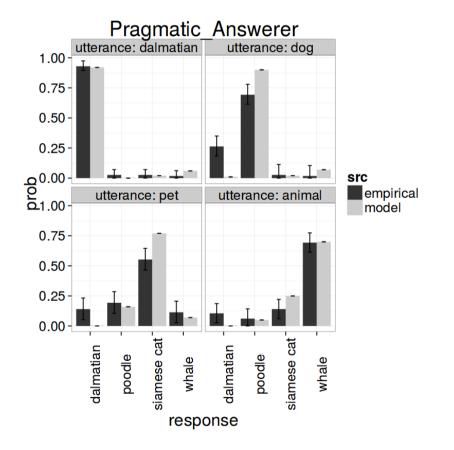


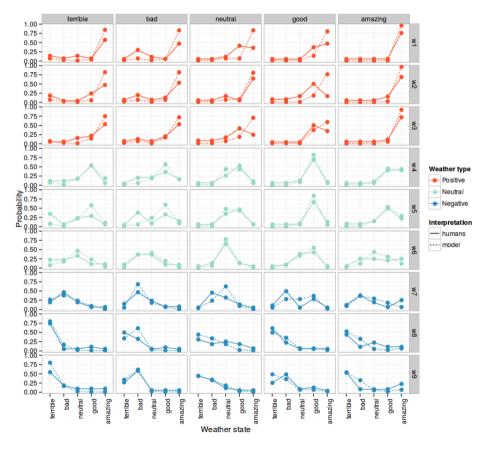
Can we learn from examples?



### Two obstacles

#### 2. Exhaustive enumeration of utterances and worlds





#### Can we generalize efficiently?

# Task: modeling color descriptions

the best color in the freakin' world!!!!!!!!

are you actually going through these answers? must be dull as all hell.

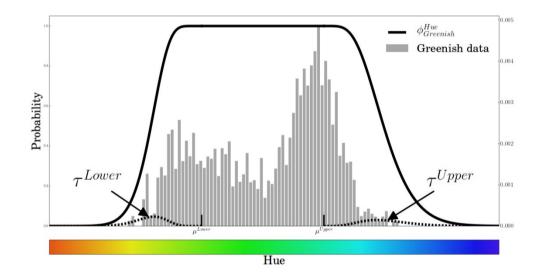
i considered rickrolling you, because i have a strong feeling no ones ever rickrolled someone with their own scientific data.

gosh, thats blue

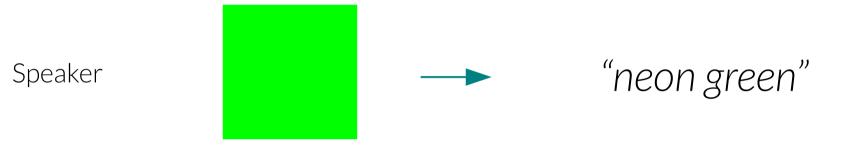
tough one... what the hell do you call this? it's pink, but not totally pink, but it's purple, but not totally purple. well, mr. xkcd, if that is your real name, thank you for what will surely stave off any hopes i have at a decent night's sleep.

day 3: sanity lost, colors keep changing but they keep staying the same...keep seeing this green, this slightly different green, mocking me...studying me...this ms green...what do you want mr green

really? this color again? i have nothing against colors personally, but this one just stands out from the rest as unusually unnattractive. i almost feel sad for it, but it made the decision to be that color so it has to find a way to deal with it



# Task: modeling color descriptions

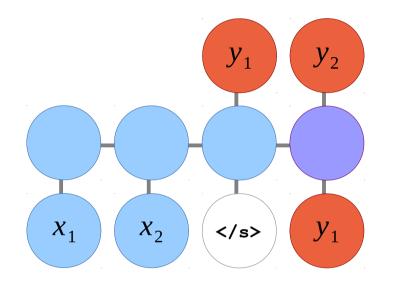


Listener

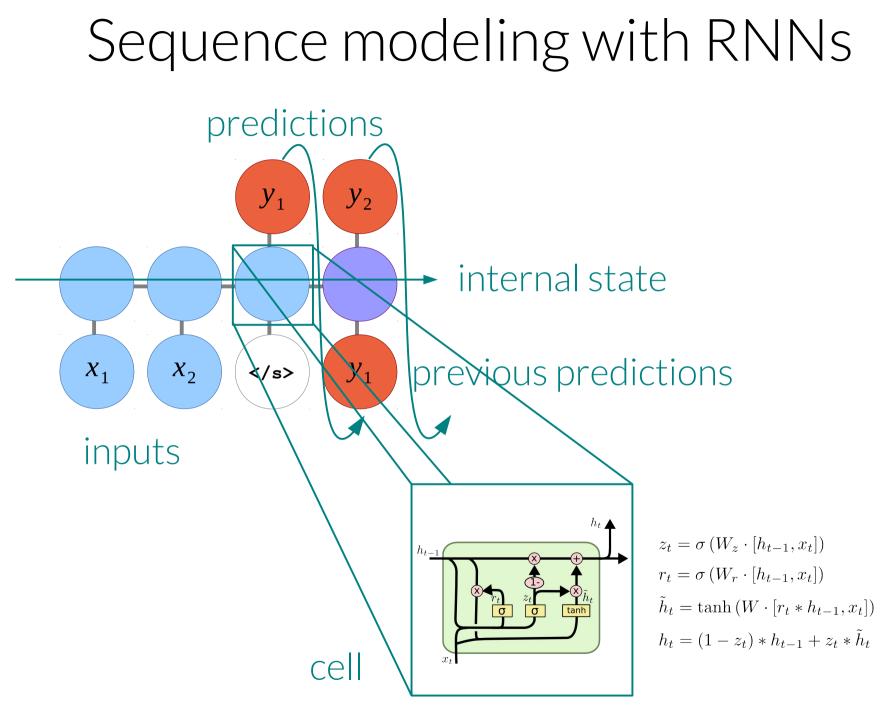
"navy blue"



### Sequence modeling with RNNs

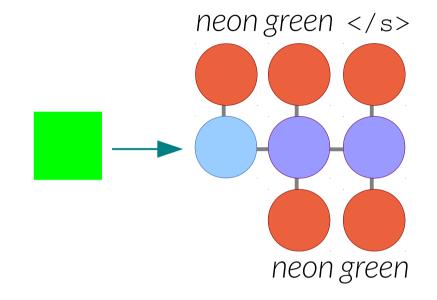


#### Sequence modeling with RNNs predictions $y_1$ *Y*<sub>2</sub> internal state previous predictions $X_1$ *X*<sub>2</sub> $y_1$ </s> inputs



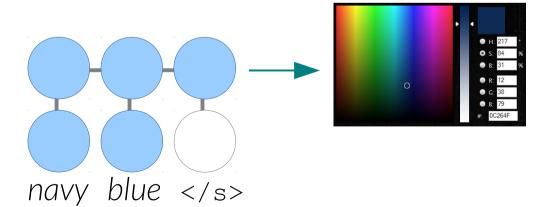
(GRU diagram by Christopher Olah)

### Speaker and listener RNNs



Speaker

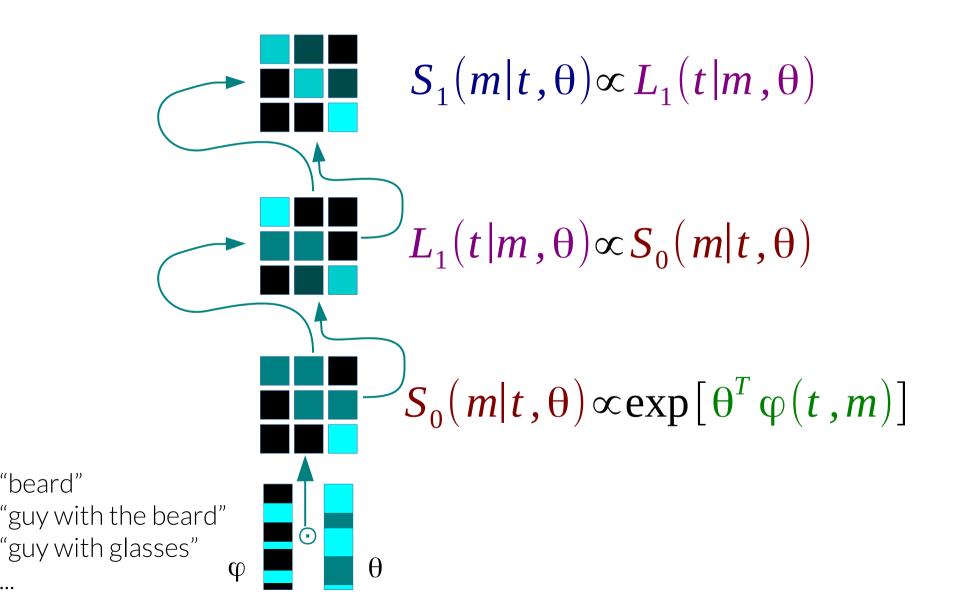


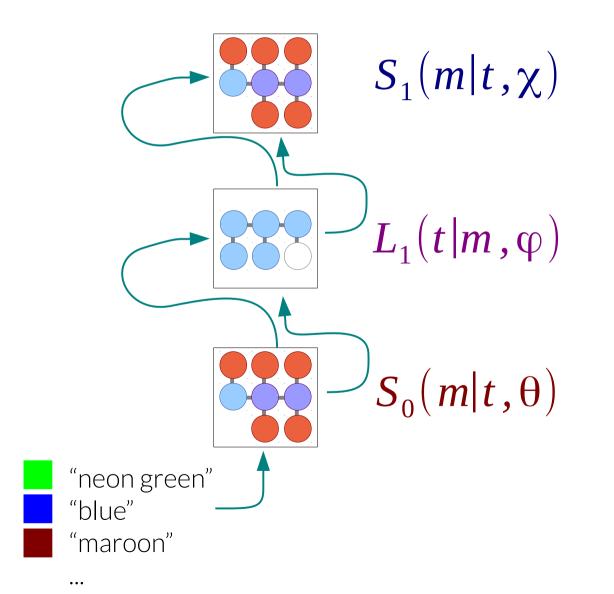


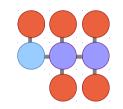
# Results: modeling color descriptions

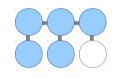
model	features	perplexity	<b>AIC</b> ( $\times 10^{6}$ )	rec@1
LSTM	Fourier	12.86	4.07	39.76%
M&S Lux	Gaussian	13.49	4.12	39.69
LSTM	buckets-4	17.83	4.58	34.96

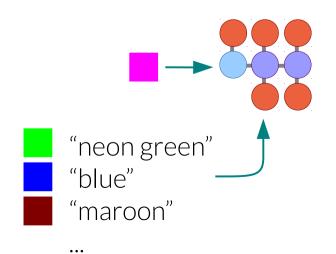
# Recap: learning through RSA

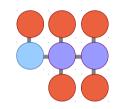


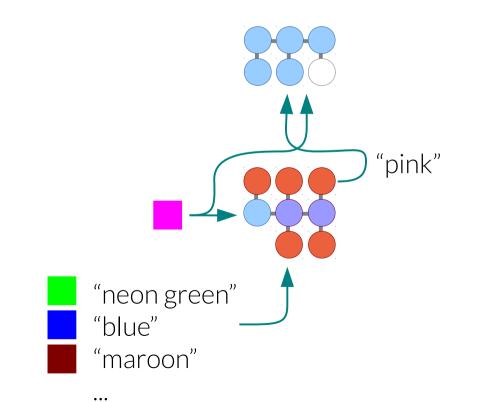


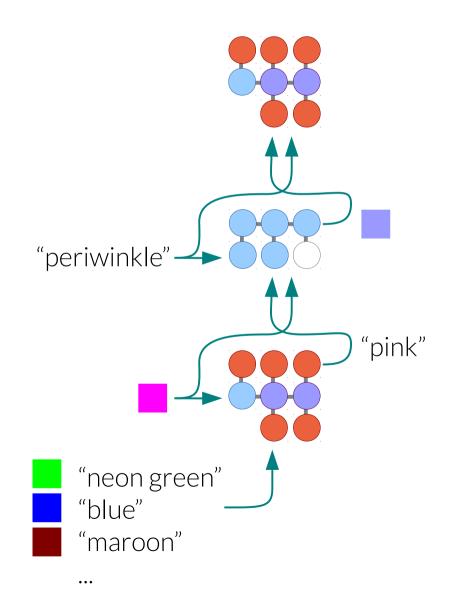


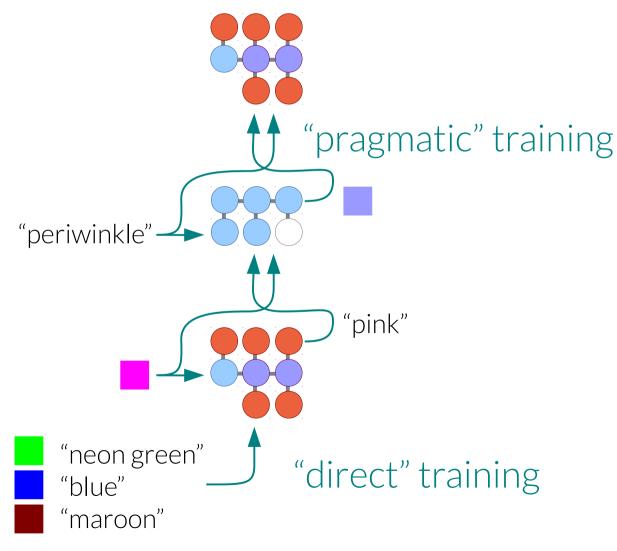












•••

### Comparing outputs Human Direct "marine blue" "navy blue" "purple" "purple" "deep green" "green" "olive" "olive green" "mauve" "dark blue"

"blue" "navy blue" "purple" "purple" "green" "green" "light green" "brown" "peach" "blue"

"bright sky blue" "almost black" "faded purple" "hot purple" "true green" "sap green" "celery" "mustard brown" "peachy pink" "marine blue"

Pragmatic

# Summary

- Combining Bayesian pragmatics and learning:
  - context-dependent disambiguation
  - capturing oddities of human language use
  - > avoiding the need for a hand-coded lexicon
- Making pragmatics scalable:
  - RNN-based sequence modeling
  - > approximate optimization of RSA-based objective
  - bootstrapping a hyper-specific generation model

# Thanks!