# Rational Speech Act models are utterance-independent updates of world priors

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### **Introduction to RSA**





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- A pragmatic listener  $L_1$ :  $u \mapsto P_{L_1}(w|u)$

$$P_{L_0}(w|u) \propto \mathbb{1}(w \ge n) \times P(w)$$

W	5	6	7
'JP ate 5 cookies'	1/3	1/3	1/3
'JP ate 6 cookies'	0	1/2	1/2
'JP ate 7 cookies'	0	0	1

$$P_{S_1}(u \mid w) \propto \frac{P_{L_0}(w \mid u)^{\alpha}}{e^{\alpha \times C(u)}}$$

(Assume  $\alpha$  = 4, and that *C*(*u*) is constant.)

W	5	6	7
'JP ate 5 cookies'	1	0.16	0.01
'JP ate 6 cookies'	0	0.84	0.06
'JP ate 7 cookies'	0	0	0.93

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W	5	6	7
'JP ate 5 cookies'	0.85	0.14	0.01
'JP ate 6 cookies'	0	0.93	0.07
'JP ate 7 cookies'	0	0	1

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- Discuss some consequences:
  - for computing RSA models;
  - for the algorithmic plausibility of RSA (Marr, 1982).

## RSA via information gain

## Kullback-Leibler (K-L) divergence (between distributions P and Q over X):

$$D_{\mathrm{KL}}(Q \parallel P) = -\sum_{x \in \mathcal{X}} Q(x) \log \left(\frac{P(x)}{Q(x)}\right)$$

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Higher values: more information is gained by going from P to Q.

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In words: if f updates P merely by *filtering* it (resulting in Q), then the information gain of Q is the negative log of the expected value of f.

• Important: the expected value of *f* is *also* the normalizing constant for *Q*:

$$Q(x) = \frac{f(x) \times P(x)}{\sum_{x'} f(x') \times P(x')}$$

$$P_{L_0}(w|u) = \frac{l(u,w) \times P(w)}{\sum_{w' \in \mathcal{W}} l(u,w') \times P(w')}$$

where l(u, w) = 1 or 0, depending on whether *u* is true at *w* 

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Let us define the *literal information gain* of *u*:

 $G_{L_0}(u) = D_{\mathrm{KL}}(P_{L_0}(w|u) || P(w))$ 

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Upshot:

- l(u, w) is our filter
- $P_{S_1}(u) \propto e^{\alpha \times (G_{L_0}(u) C(u))}$  is our *new* "prior"!

#### Reformulating the pragmatic speaker: example

 $\llbracket$ 'JP ran  $u \operatorname{km'} \rrbracket = w \ge u$ 

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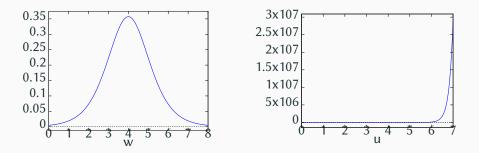
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Prior over JP's running distance

 $P_{S_1}(u|w=7)$  with  $\alpha = 4$ 

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the *specificity* of *w* 

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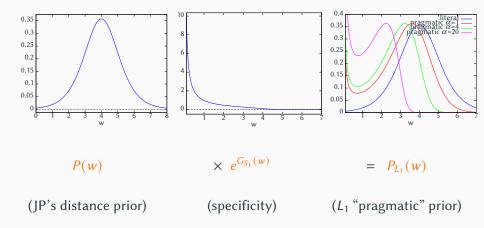
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Define  $P_{L_1}(w) = e^{G_{S_1}(w)} \times P(w)$  as our *new* prior! Upshot:

$$P_{L_1}(w|u) \propto l(u,w) \times P_{L_1}(w)$$

#### Reformulating the pragmatic listener: example



Some consequences

## **Computing RSA models**

Main result:

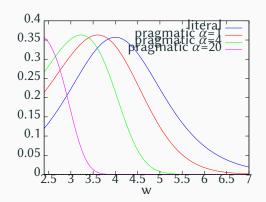
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The "pragmatic" interpretation of 'JP ran 2.4 km' is gotten by simply cropping  $P_{L_1}(w)$  and normalizing:

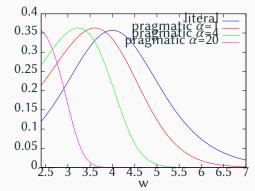


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(Side note: the expected implicature is generated for large  $\alpha$  only!) 14

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(RSA-style) pragmatic interpretations can be *learned*, just as probability distributions over events can; pragmatic distributions are additionally sensitive to an event's specificity.

# References

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