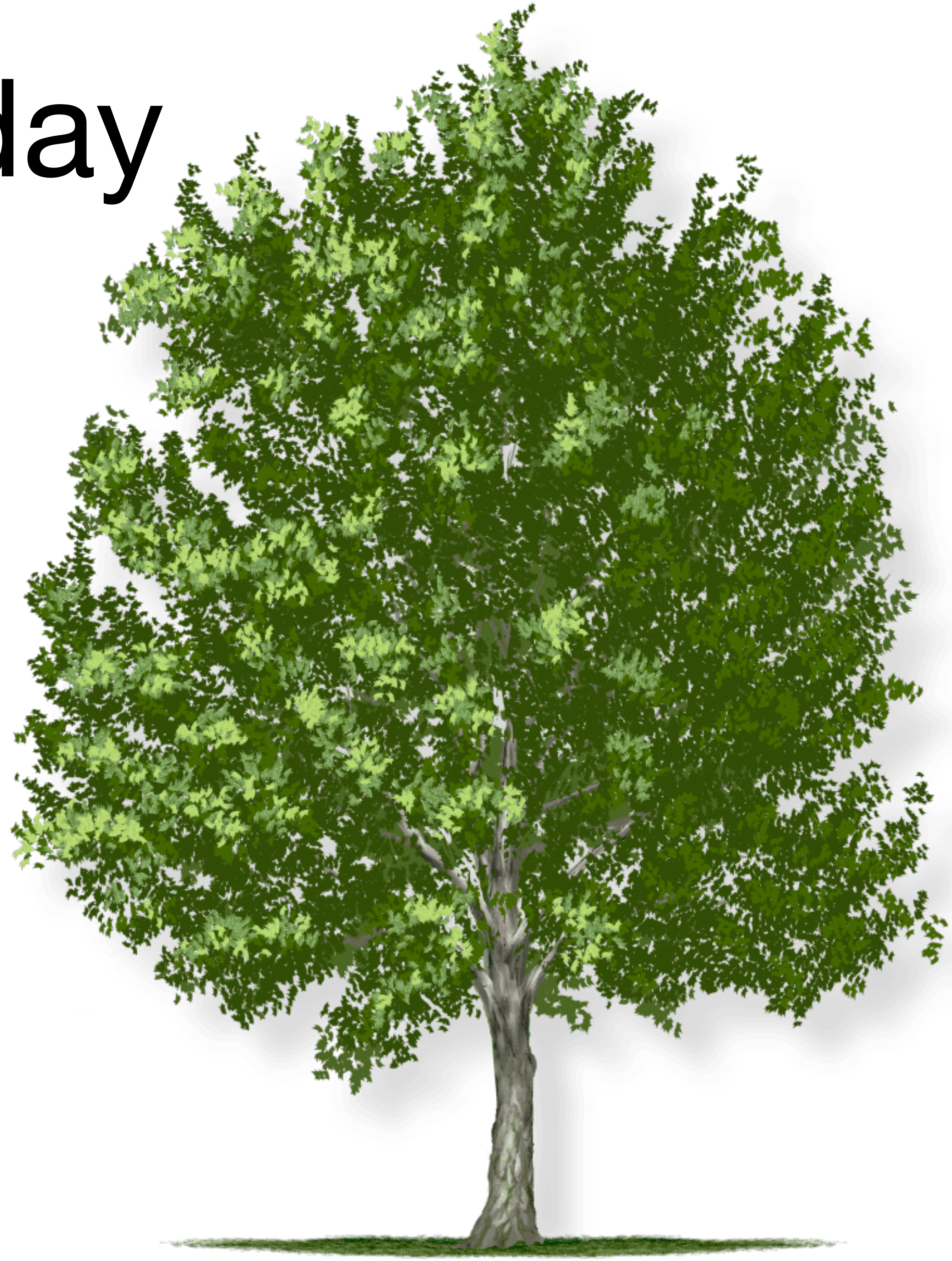
Politeness and the Structure of Conversation

w/ Julia Minson, Francesca Gino, Martha Jeong, Hanne Collins, Frances Chen, Alejandro Kantor & Dustin Tingley

Themes for Today



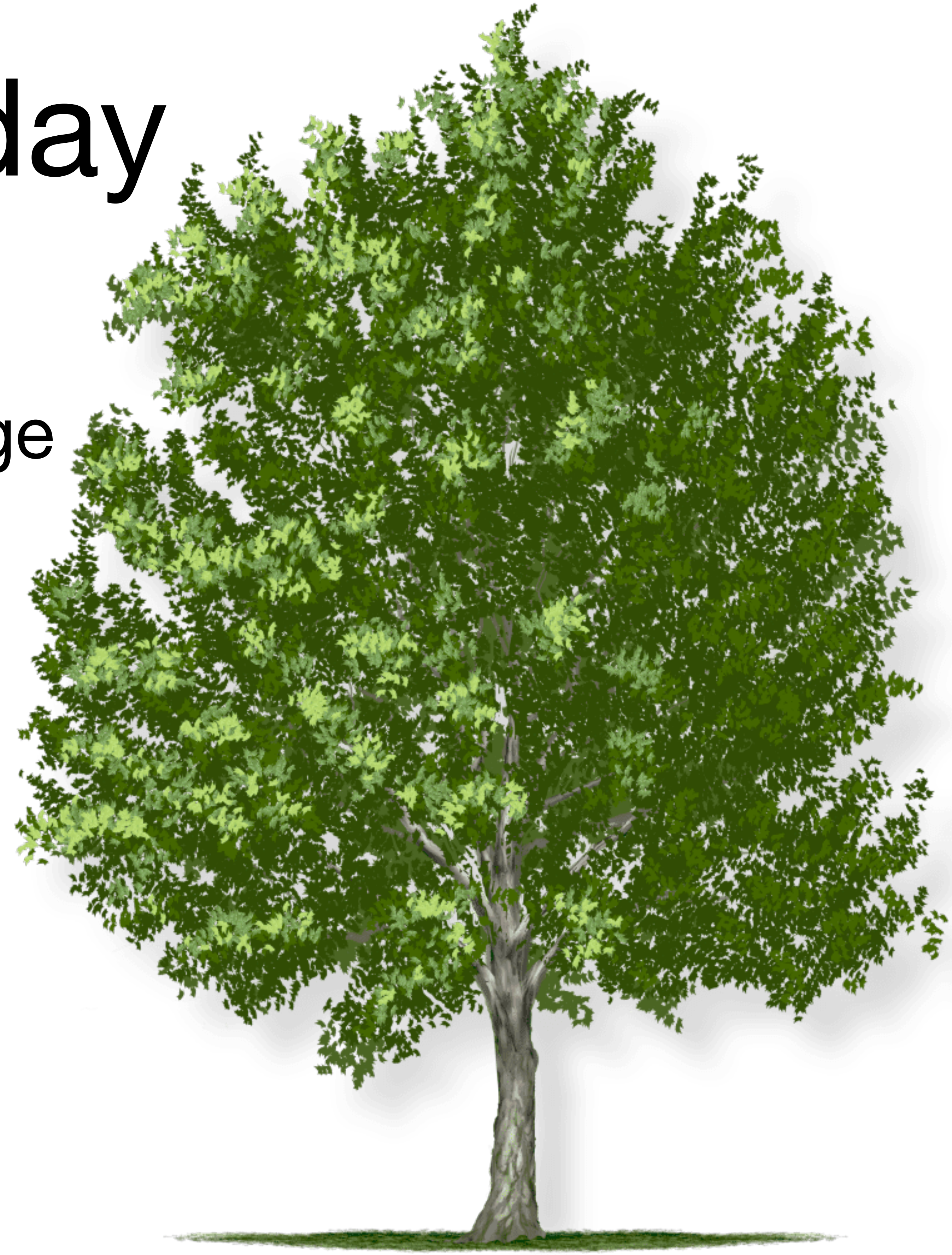
Themes for Today

Revealing the hidden
structure of social language

Themes for Today

Revealing the hidden structure of social language

Constructing workflows for reproducible text analysis

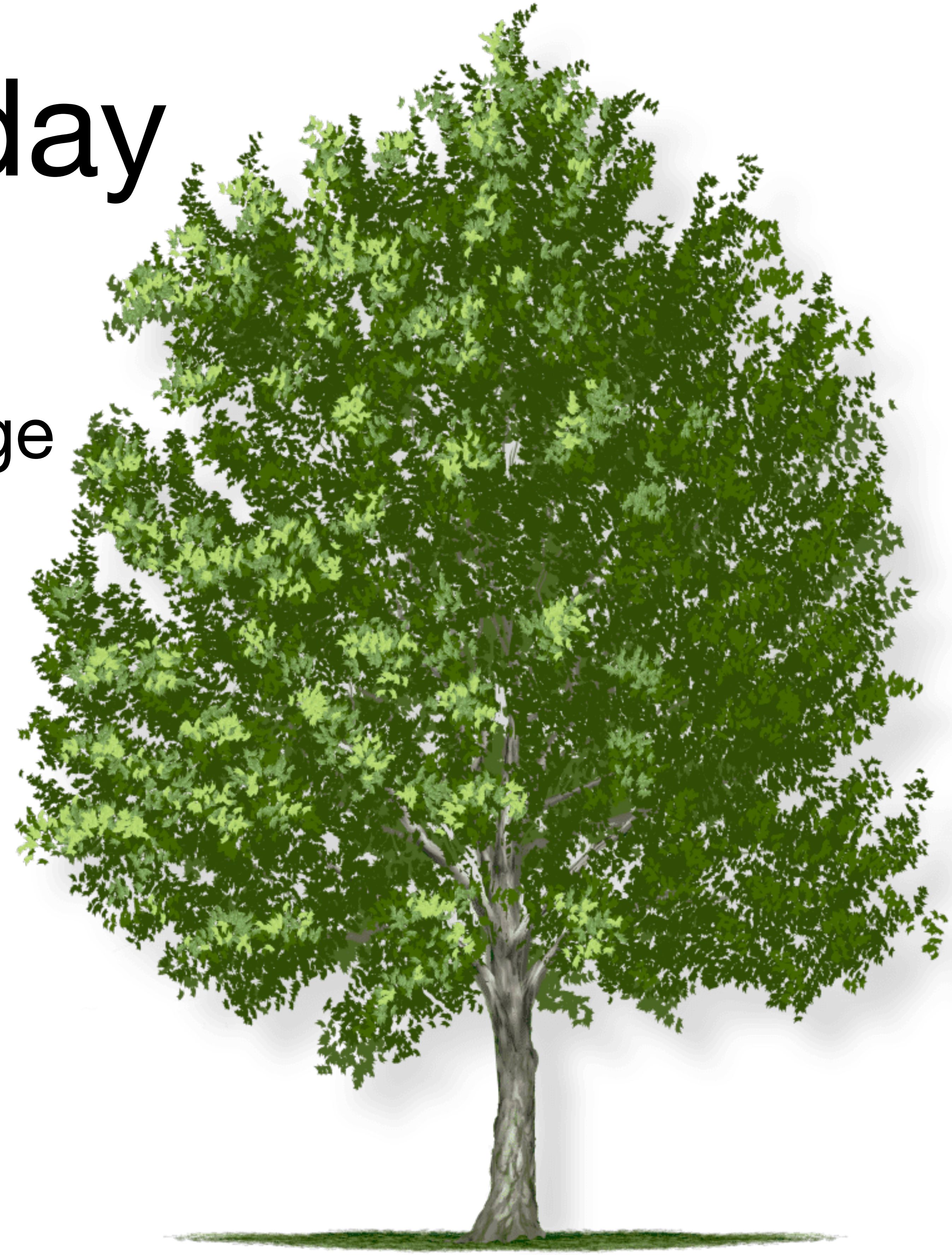


Themes for Today

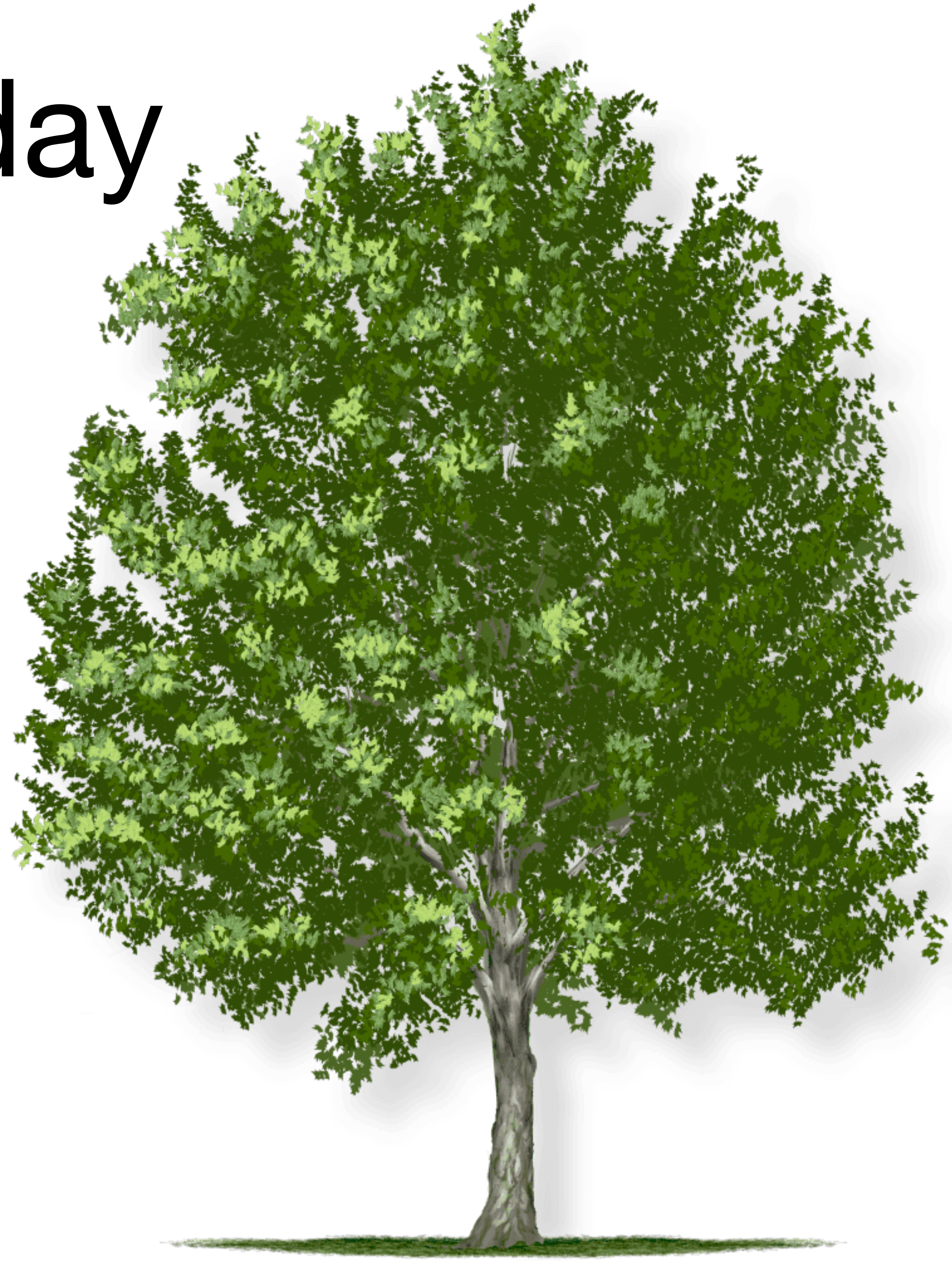
Revealing the hidden structure of social language

Constructing workflows for reproducible text analysis

Building a more cumulative scientific community



Themes for Today



Themes for Today

Hidden structure

What are the roots?

What are the roots?

Politeness: an R Package

http://www.mikeyeomans.info/politeness

What are the roots?

Politeness: an R Package

politeness()
politenessPlot()
politenessProjection()
findPoliteTexts()

http://www.mikeyeomans.info/politeness

What are the leaves?

Negotiations

Communicating Warmth in Distributive Negotiations is Surprisingly Counter-Productive

(Jeong et al., 2018)

What are the leaves?

Negotiations

Communicating Warmth in Distributive Negotiations is Surprisingly Counter-Productive

(Jeong et al., 2018)

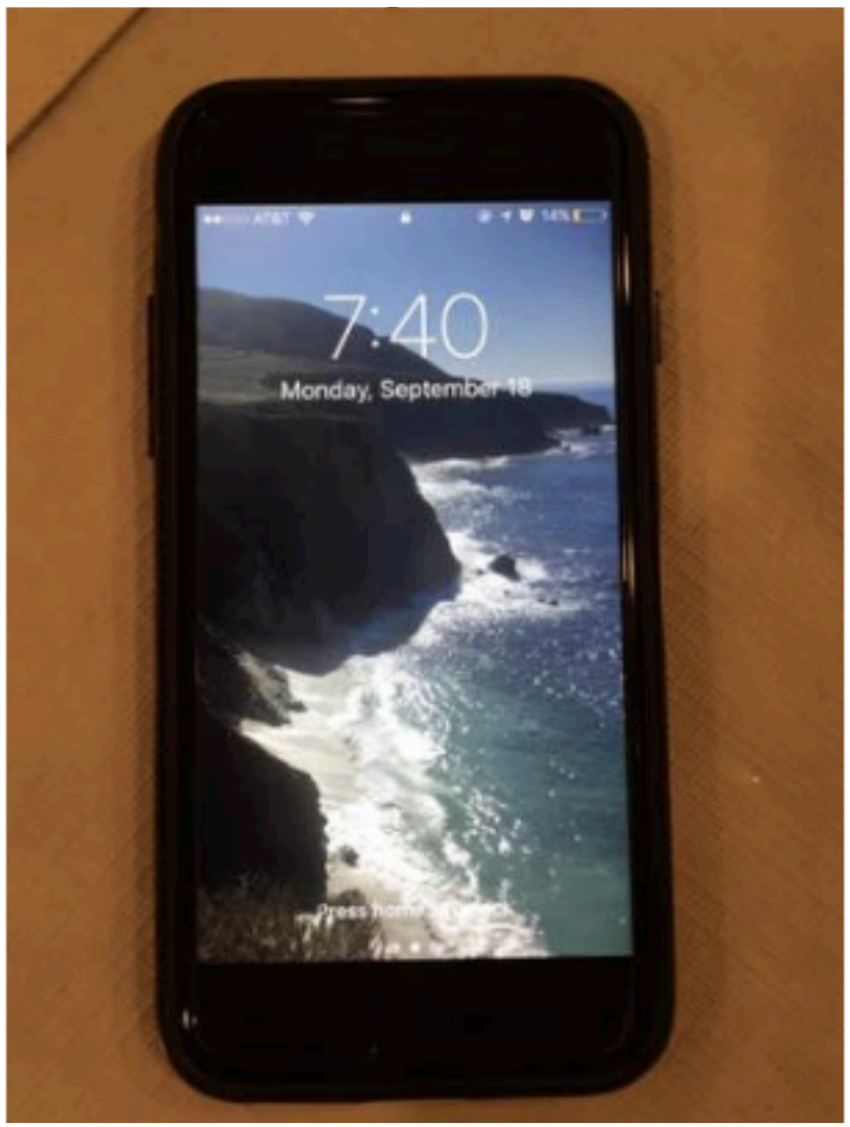
Organizational Conflict

Conversational Receptiveness: Improving Engagement with Opposing Views

(Yeomans et al., 2020)

Let's Make a Deal

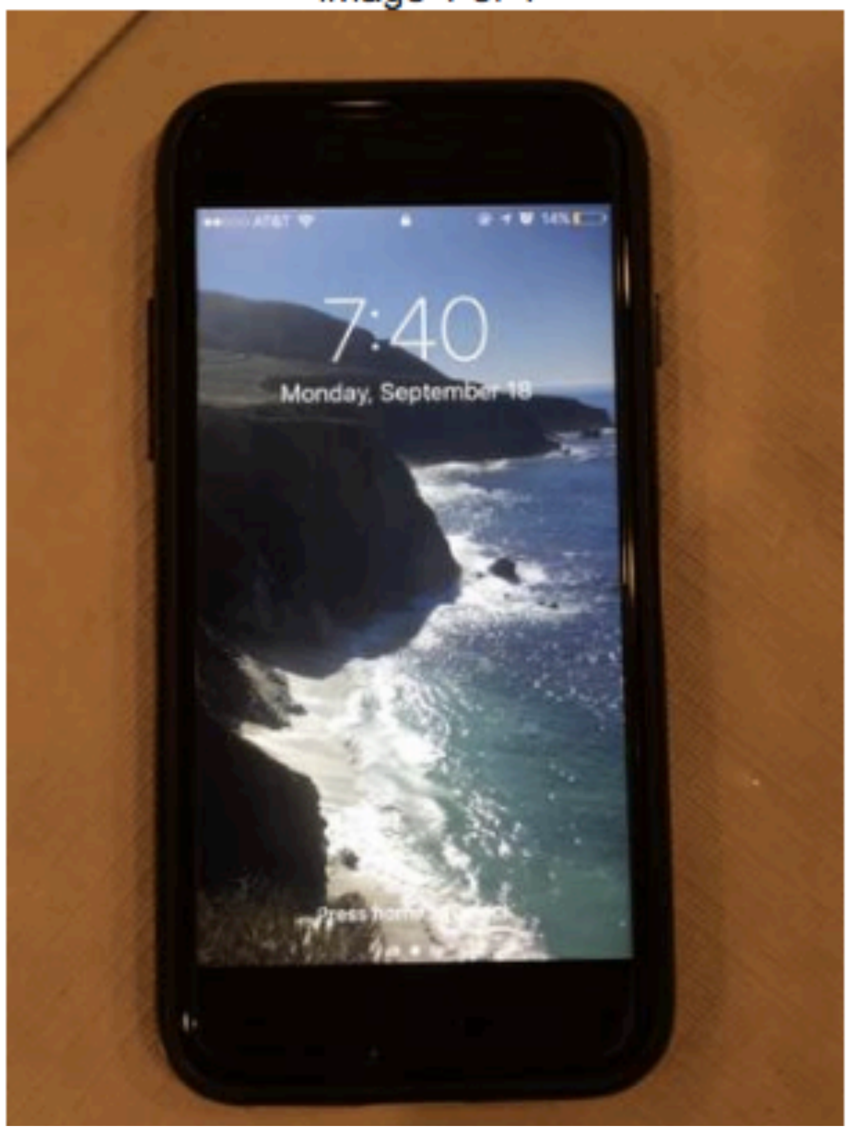
Let’s Make a Deal



Let’s Make a Deal

☆ **Iphone 7 - Unlocked - 128 gb - Excellent condition!!! - $550** **(Cambridge ma)**

image 1 of 4



condition: **excellent**

make / manufacturer: **Apple**

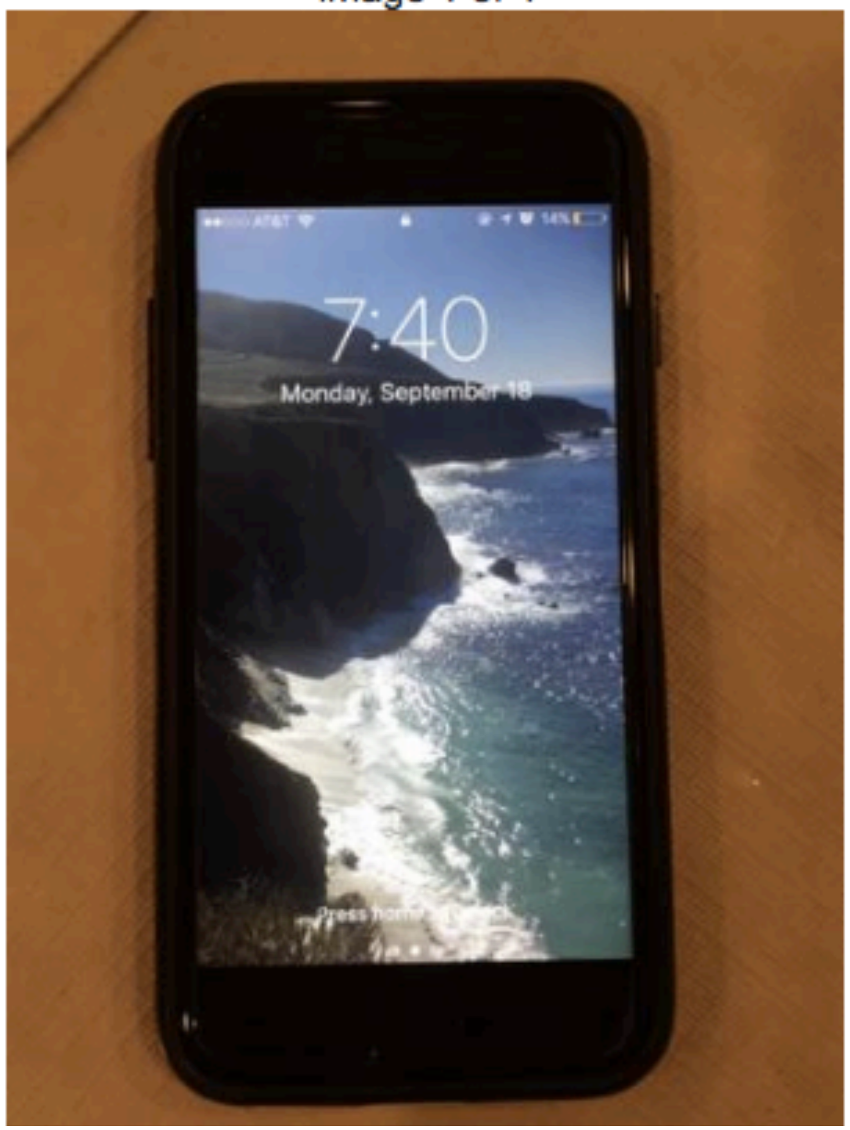
mobile OS: **apple iOS**

model name / number: **Iphone 7**

Let's Make a Deal

Iphone 7 - Unlocked - 128 gb - Excellent condition!!! - $550 (Cambridge ma)

image 1 of 4



condition: **excellent**

make / manufacturer: **Apple**

mobile OS: **apple iOS**

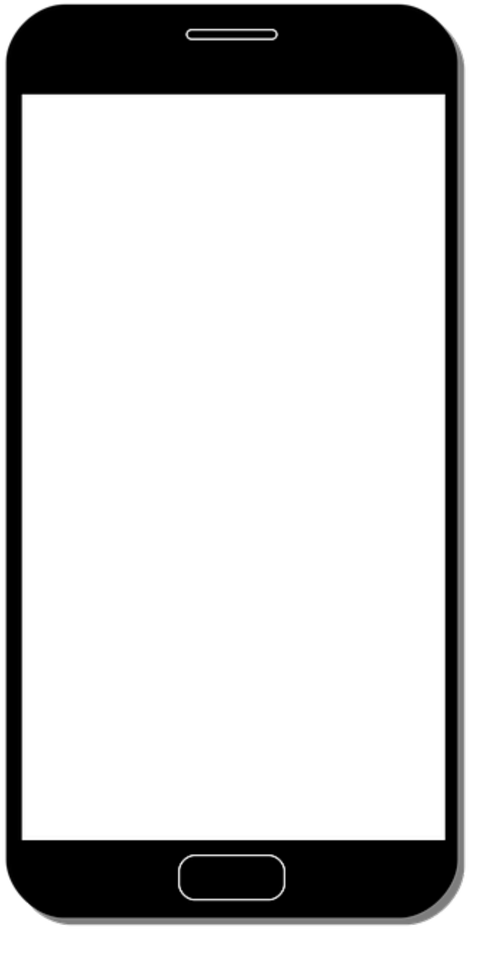
model name / number: **Iphone 7**

Iphone 7
• 128 GB
•Matte Black
•Unlocked for any carrier.
•Comes with original box and all original accessories.
• Extra glass screen protector and case included!

Used originally on AT&T. Phone is in excellent condition. Has had a screen protector on and in a case since purchase. Upgrading phone so I am selling this one. NO TRADES!! Local pick up or delivery only!!!

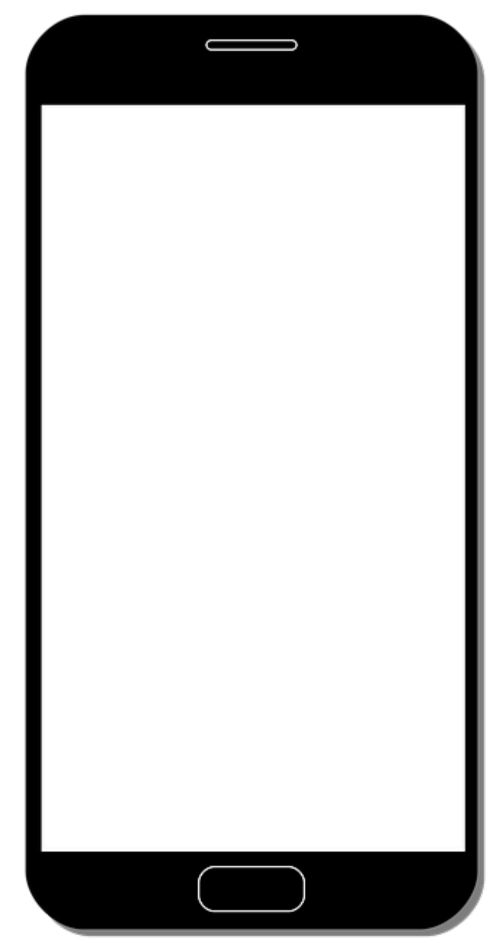
Let’s Make a Deal

$450



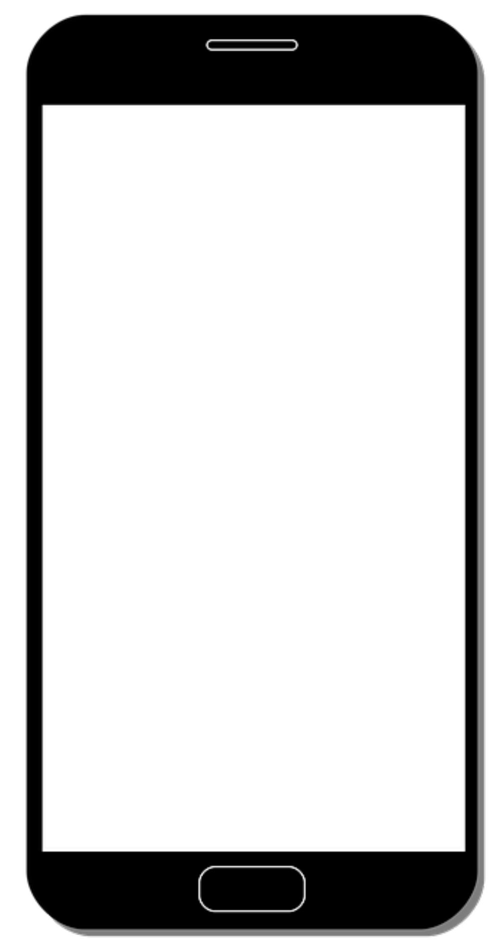
Let’s Make a Deal

I can pick it up
from you.
I can
pay $450 in cash for the phone.
I can
meet you whenever.



Let’s Make a Deal

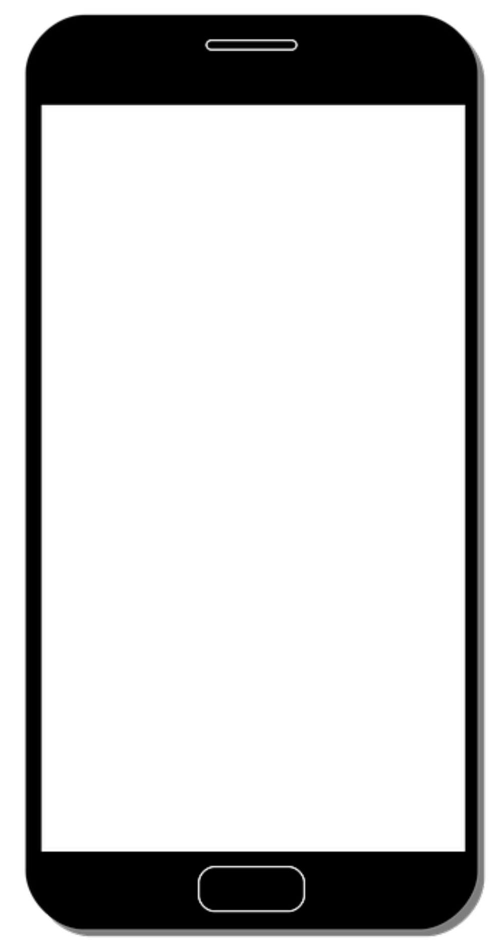
I can pick it up from you, but your asking price is too high I can only afford to pay $450 in cash for the phone. That’s my absolute limit. I can meet you whenever.



Let's Make a Deal

I was looking at your post and I would be interested in purchasing your phone. I can pick it up from you, but your asking price is too high I can only afford to pay $450 in cash for the phone. That's my absolute limit. I can meet you whenever. Let me know if this will work.

Riley



Let's Make a Deal

Hello, I was looking at your post and

I

would be interested in purchasing your

phone. I can pick it up

from you, but your asking

price is too high I can only afford to

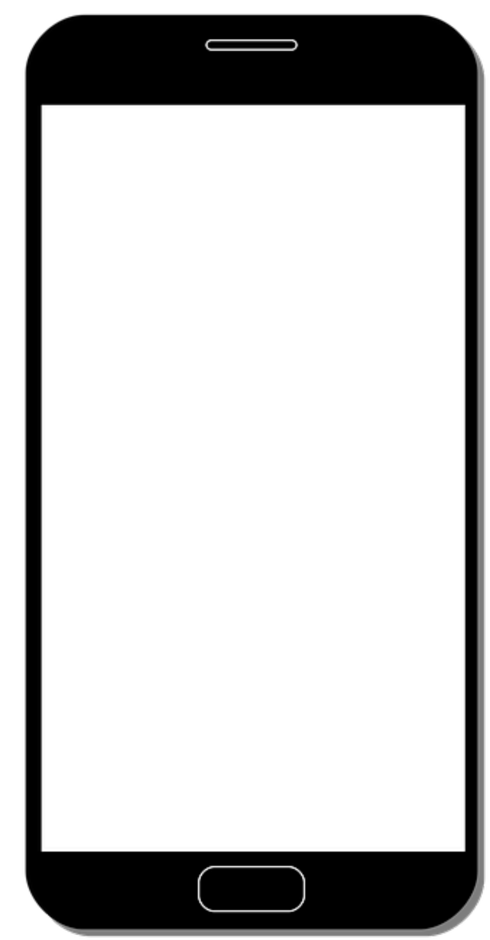
pay $450 in cash for the phone. That's my

absolute limit. I can

meet you whenever.

Let me know if this will work.

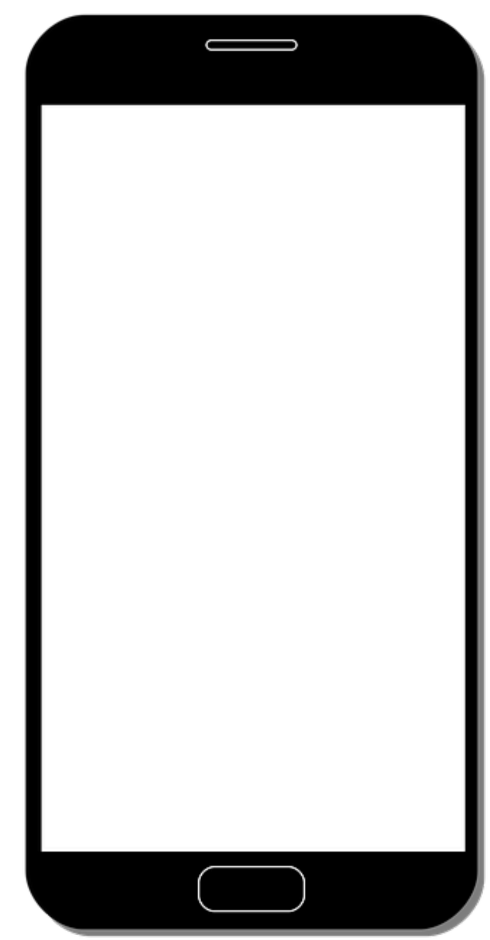
Thank you, Riley



Let’s Make a Deal

Hello, I was looking at your post and this phone is the one I’ve been waiting for! I would be interested in purchasing your beautiful phone. I can pick it up from you, but your asking price is too high I can only afford to pay $450 in cash for the phone. That’s my absolute limit. I can meet you whenever. Let me know if this will work.

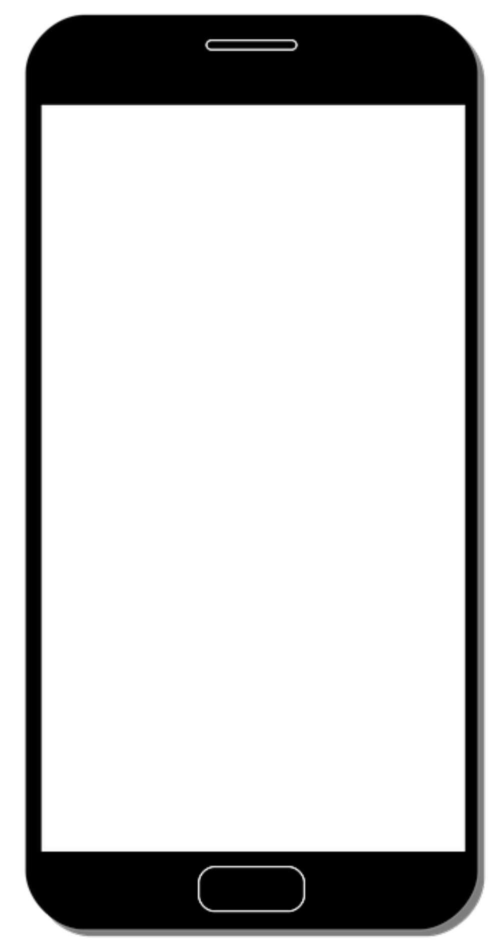
Thank you, Riley



Let’s Make a Deal

Hello, I was looking at your post and this phone is the one I’ve been waiting for! I would be interested in purchasing your beautiful phone. I am happy to pick it up from you, but your asking price is too high. I can only afford to pay $450 in cash for the phone. That’s my absolute limit. I can meet you whenever. Let me know if this will work for you, and have a great day.

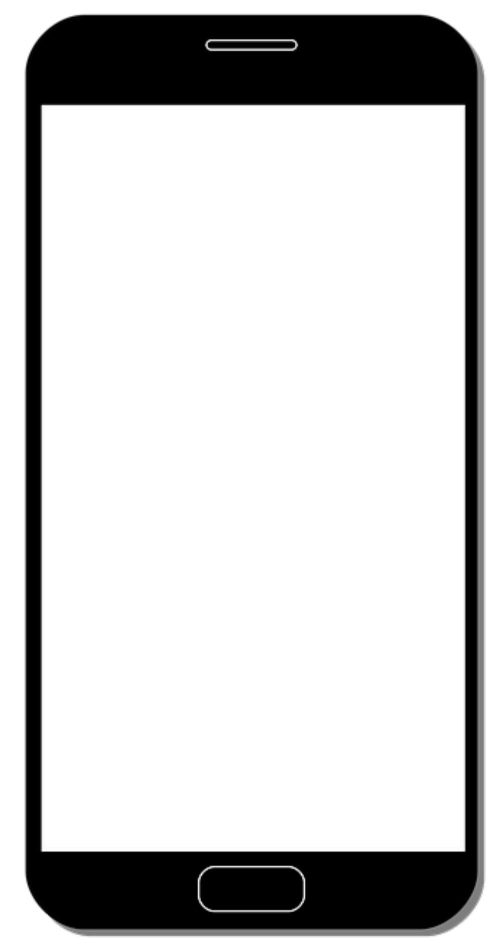
Thank you, Riley



Let’s Make a Deal

Hello, I was looking at your post and this phone is the one I’ve been waiting for! I would be interested in purchasing your beautiful phone. I am happy to pick it up from you, but unfortunately your asking price is too high for me. I can only afford to pay $450 in cash for the phone. That’s my absolute limit, I’m sorry to say. I can meet you whenever. Let me know if this will work for you, and have a great day.

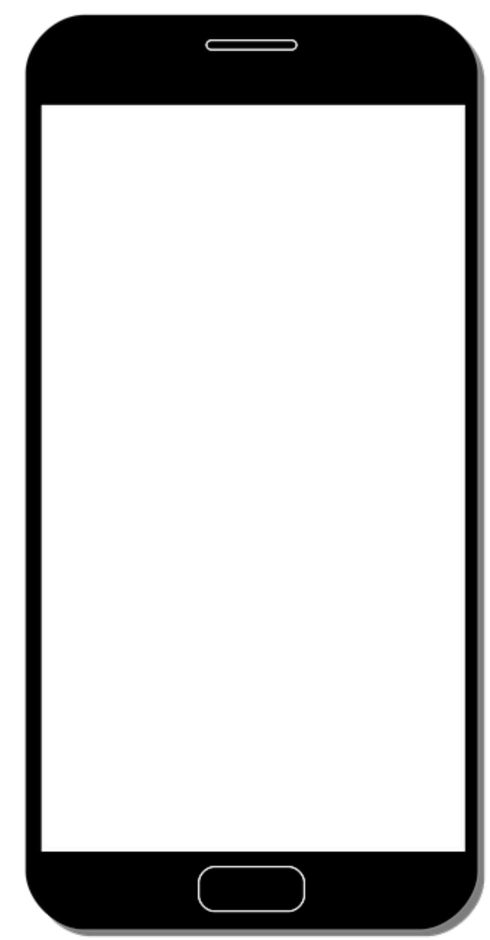
Thank you, Riley



Let's Make a Deal

Hello, I was looking at your post and this phone is the one I've been waiting for! I would be interested in purchasing your beautiful phone. I am happy to pick it up from you, but unfortunately your asking price is too high for me. I can only afford to pay $450 in cash for the phone. That's my absolute limit, I'm sorry to say. And I can meet you whenever is most convenient for your schedule. Let me know if this will work for you, and have a great day.

Thank you, Riley

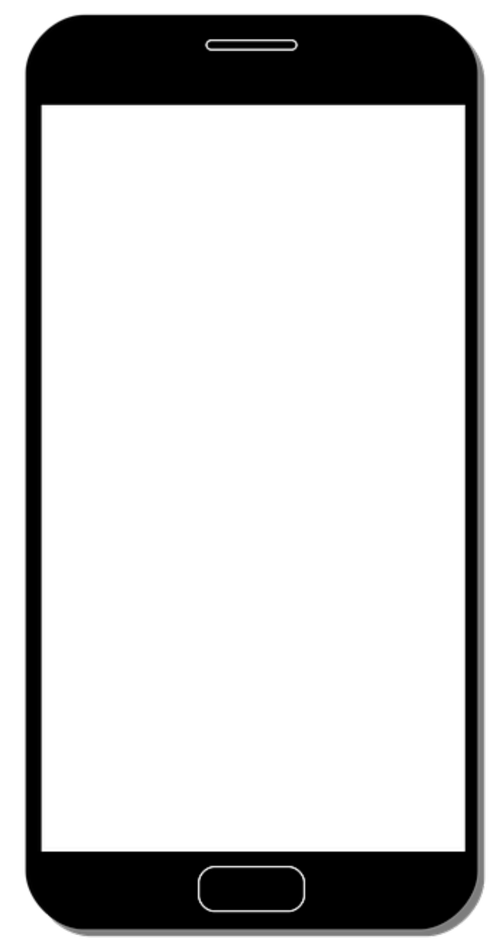


Let’s Make a Deal

I was looking at your post and I would be interested in purchasing your phone. I can pick it up from you, but your asking price is too high I can only afford to pay $450 in cash for the phone. That’s my absolute limit. I can meet you whenever.

Let me know if this will work.

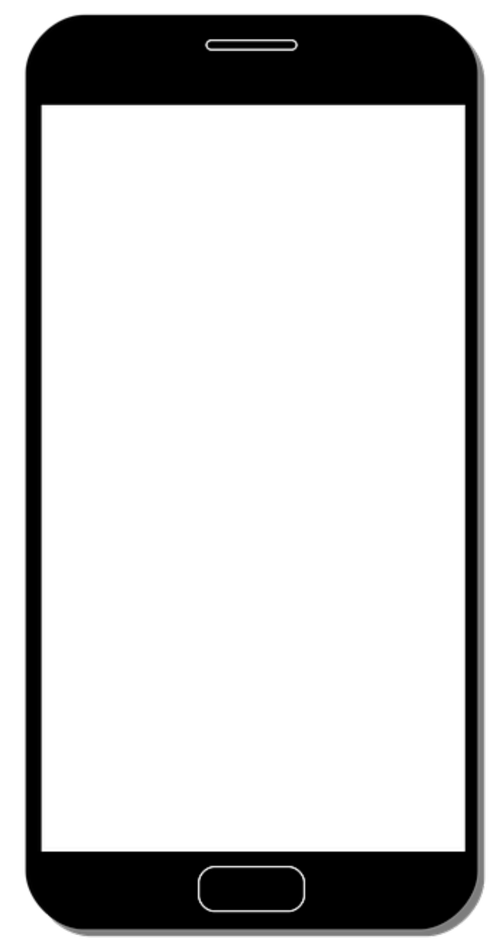
Riley



Let’s Make a Deal

I was looking at your post and I would be interested in taking this off your hands. I can pick it up from you, but your asking price is too high. I can only afford to pay $450 in cash for the phone. That’s my absolute limit, non-negotiable. I can meet you any time. Let me know if this will work for you.

Riley

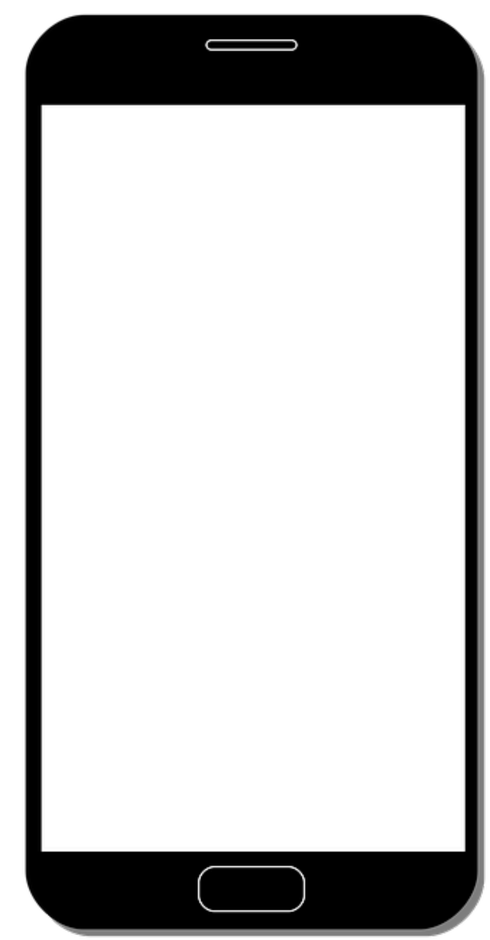


Let's Make a Deal

I was looking at your post and this phone could meet my needs. I would be interested in taking this off your hands. I am willing to pick it up from you, but your asking price is too high. I can only afford to pay $450 in cash for the phone. That's my absolute limit, non-negotiable. I can meet you any time.

Let me know if this will work for you.

Riley



Communicating Warmth in Distributive Negotiations is Surprisingly Counter-Productive

(Jeong, Minson, Yeomans & Gino, 2018)

Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers garner worse counteroffers

Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers garner worse counteroffers

- natural field experiment audit study

Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers garner worse counteroffers

- natural field experiment audit study
- 775 iPhone sellers from 15 US cities in May/June 2017

Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers garner worse counteroffers

- natural field experiment audit study
- 775 iPhone sellers from 15 US cities in May/June 2017

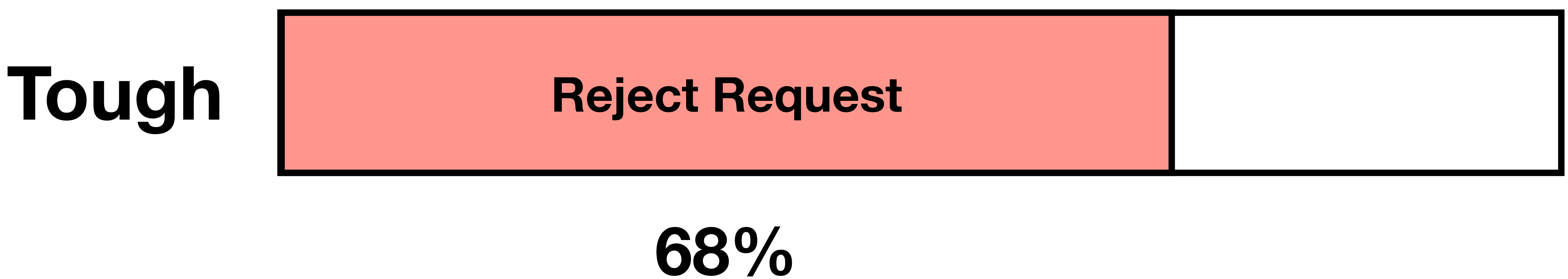
Tough

Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers garner worse counteroffers

- natural field experiment audit study
- 775 iPhone sellers from 15 US cities in May/June 2017

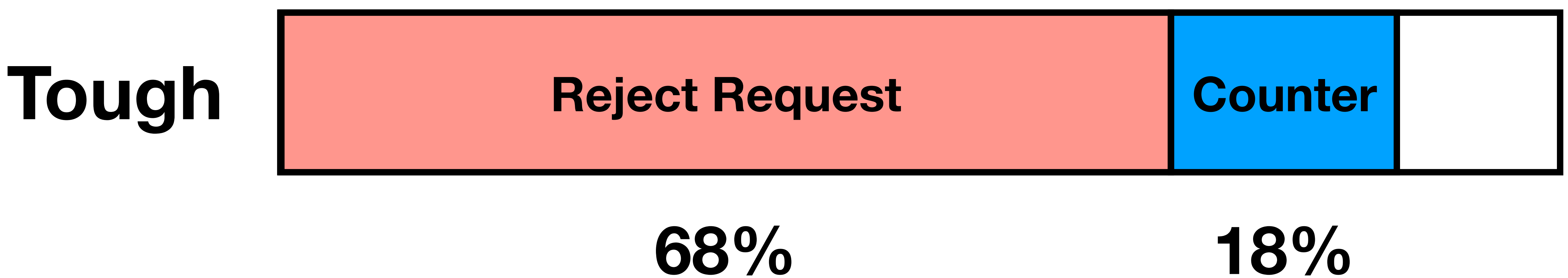


Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers garner worse counteroffers

- natural field experiment audit study
- 775 iPhone sellers from 15 US cities in May/June 2017

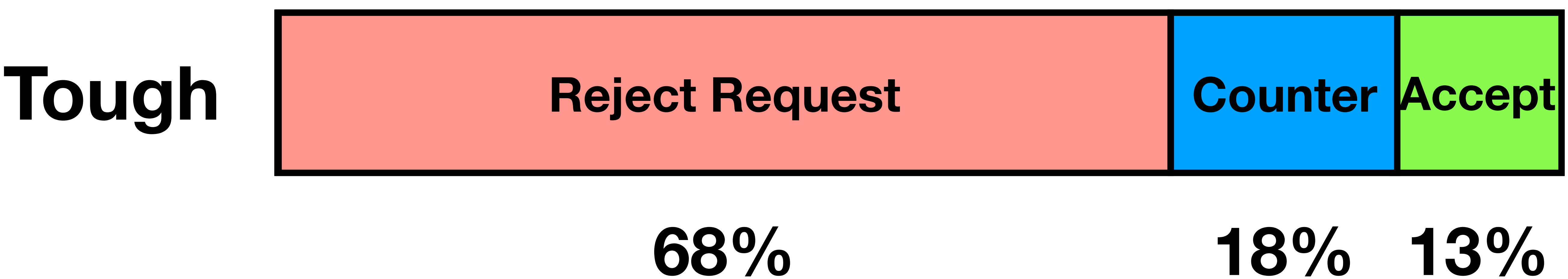


Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers garner worse counteroffers

- natural field experiment audit study
- 775 iPhone sellers from 15 US cities in May/June 2017

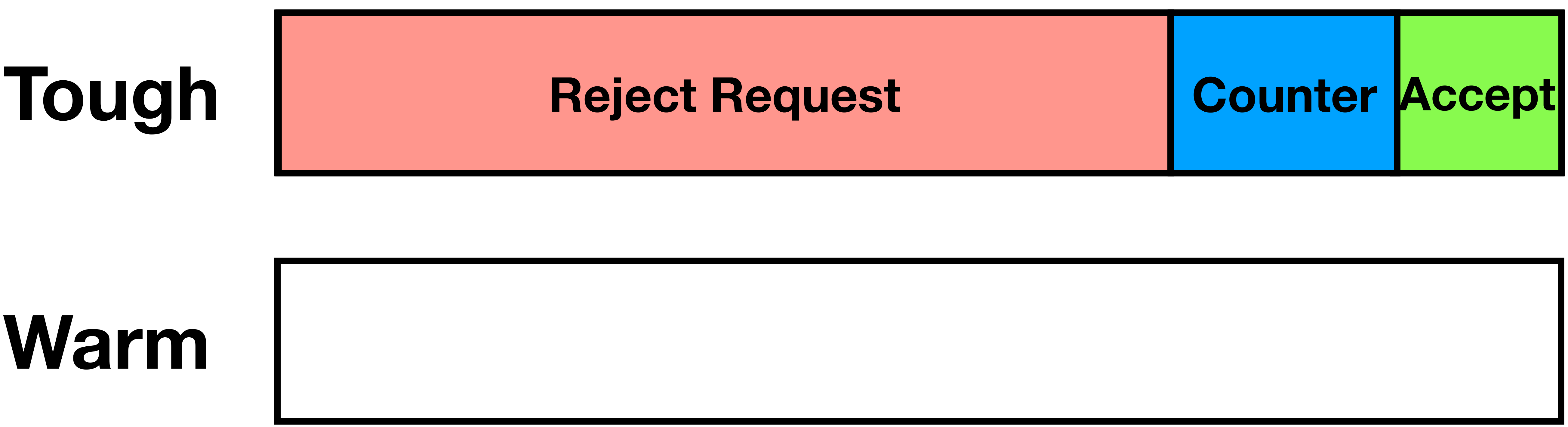


Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers garner worse counteroffers

- natural field experiment audit study
- 775 iPhone sellers from 15 US cities in May/June 2017

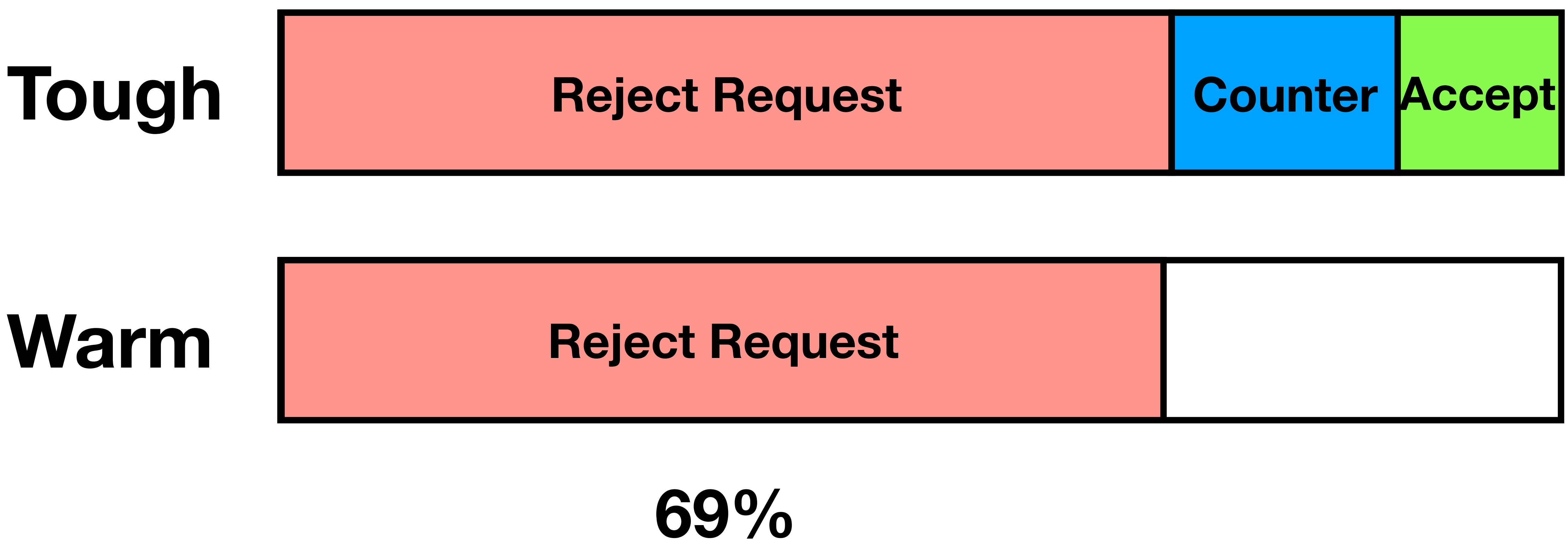


Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers garner worse counteroffers

- natural field experiment audit study
- 775 iPhone sellers from 15 US cities in May/June 2017

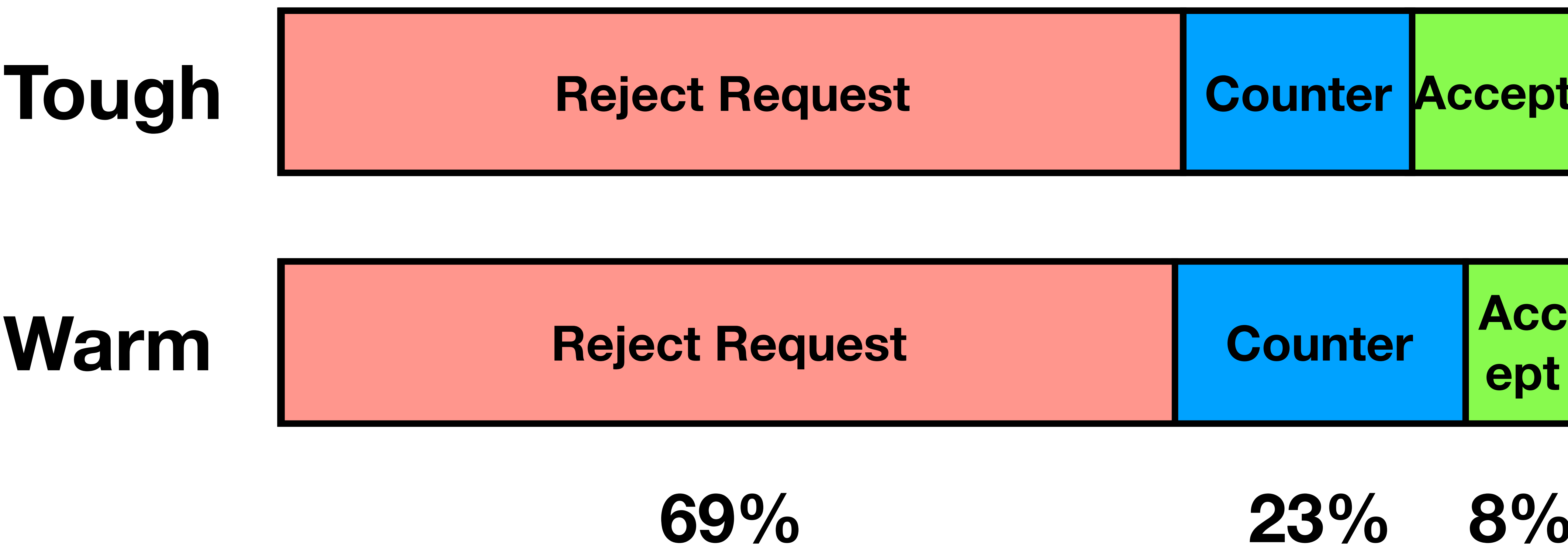


Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers garner worse counteroffers

- natural field experiment audit study
- 775 iPhone sellers from 15 US cities in May/June 2017



Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers earn worse final deals

Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers earn worse final deals

- incentivized lab experiment with dyads

Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers earn worse final deals

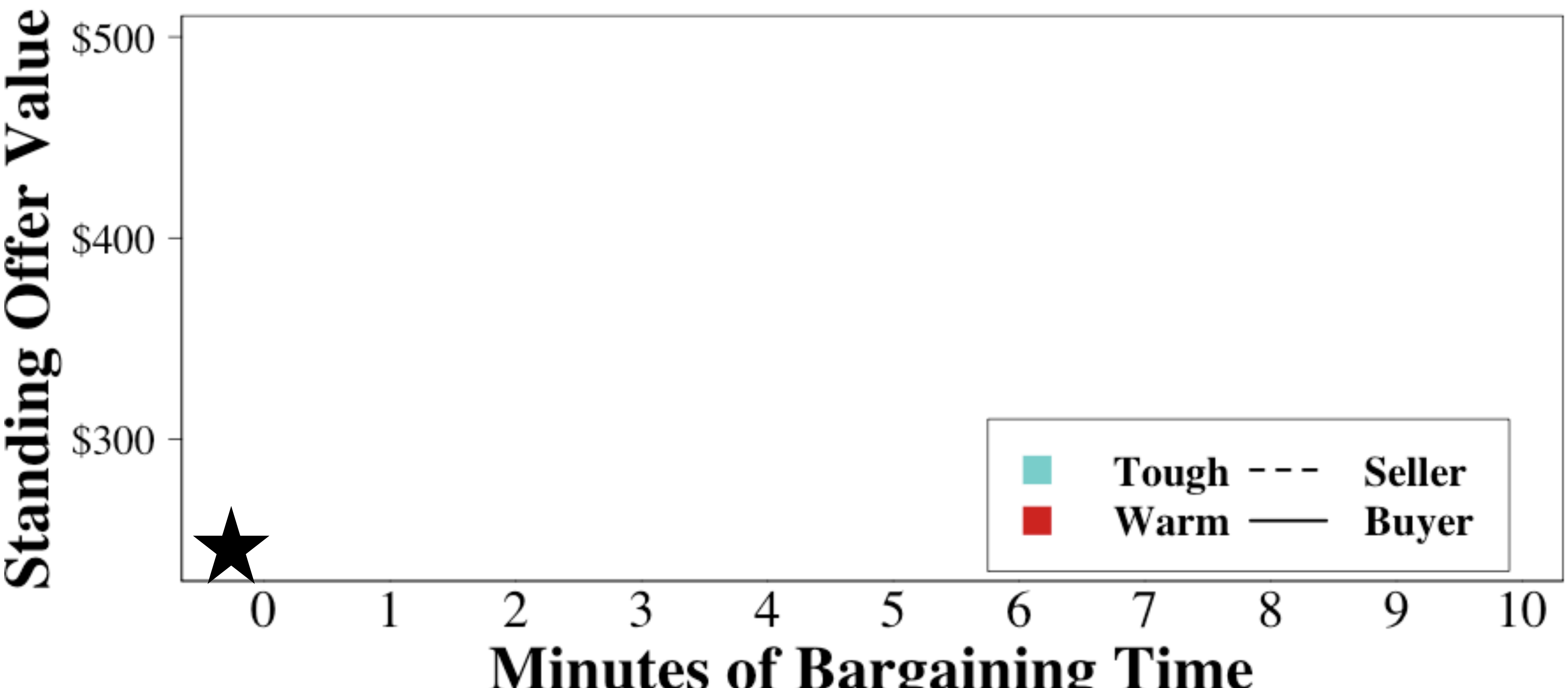
- incentivized lab experiment with dyads
- driven by early seller concessions

Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers earn worse final deals

- incentivized lab experiment with dyads
- driven by early seller concessions

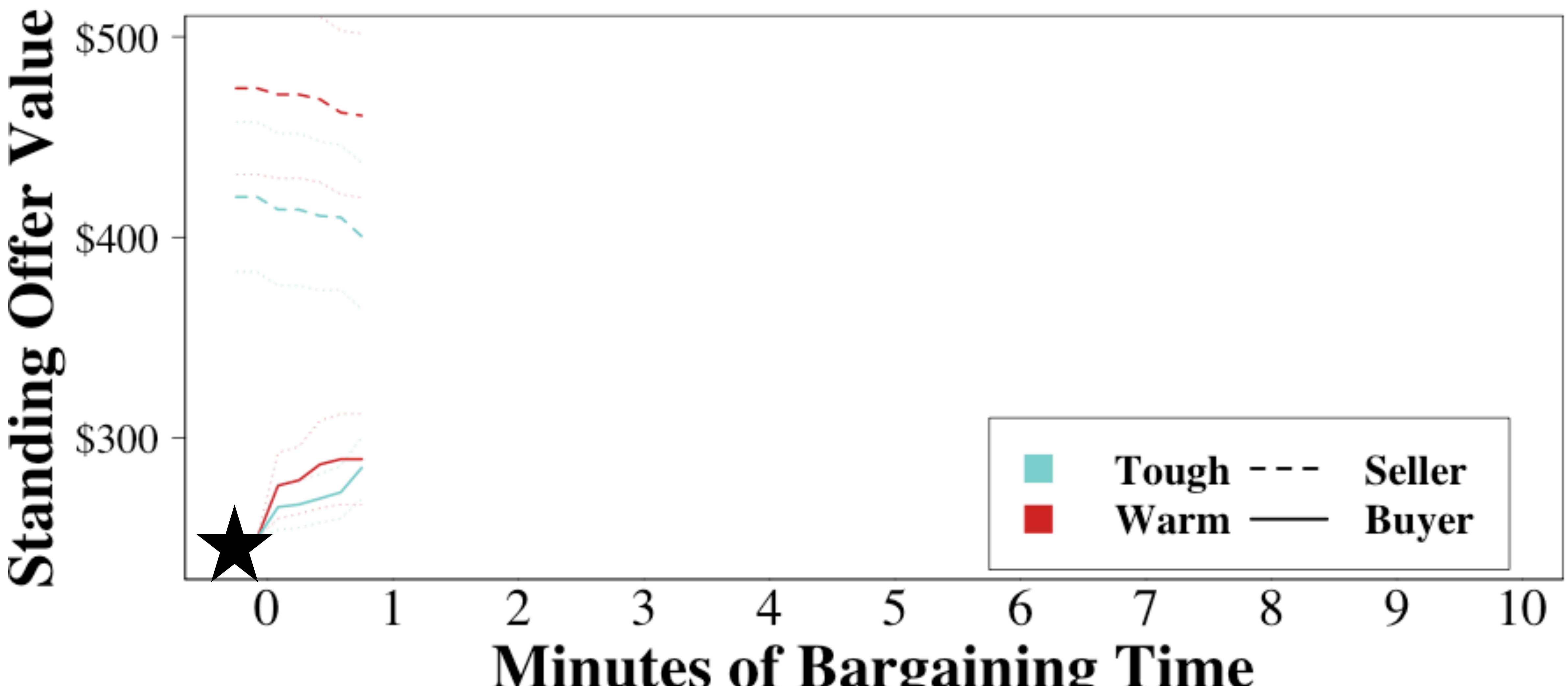


Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers earn worse final deals

- incentivized lab experiment with dyads
- driven by early seller concessions

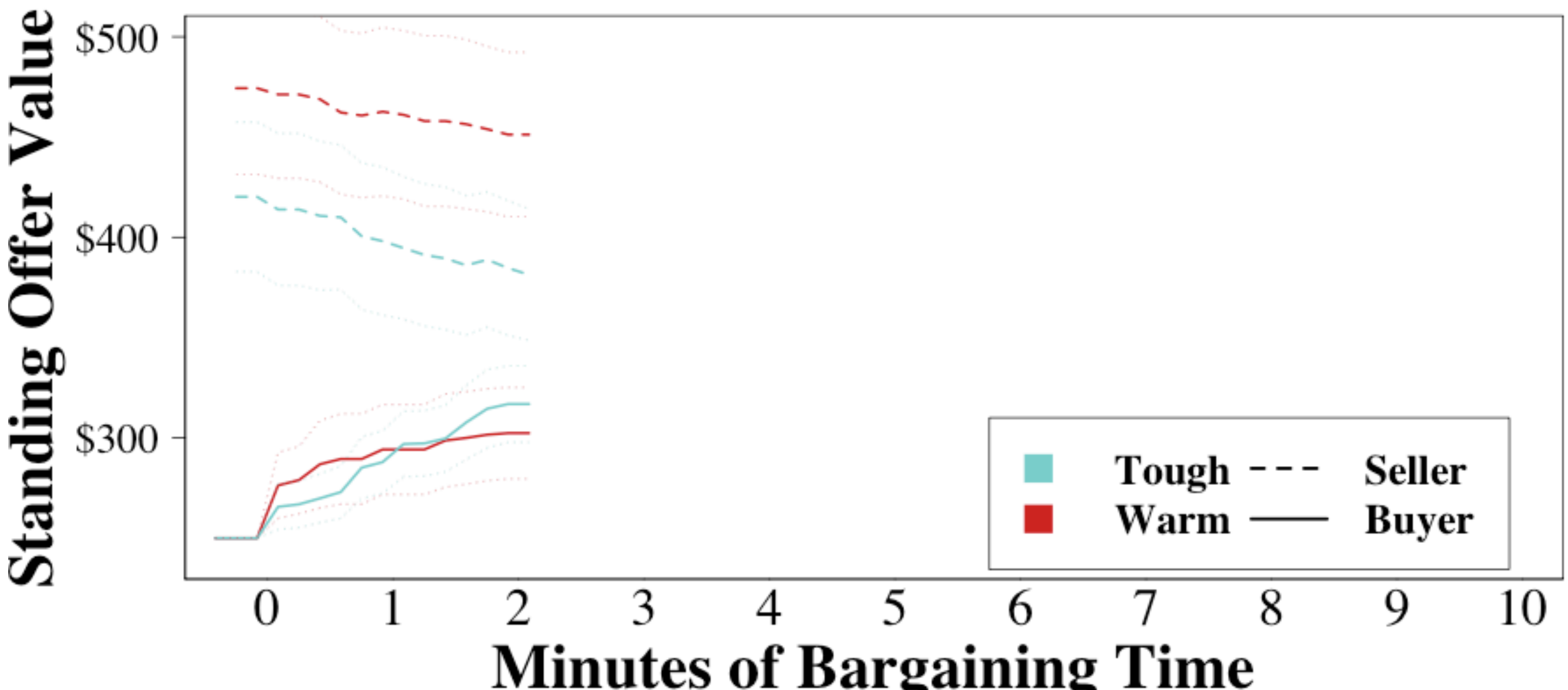


Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers earn worse final deals

- incentivized lab experiment with dyads
- driven by early seller concessions

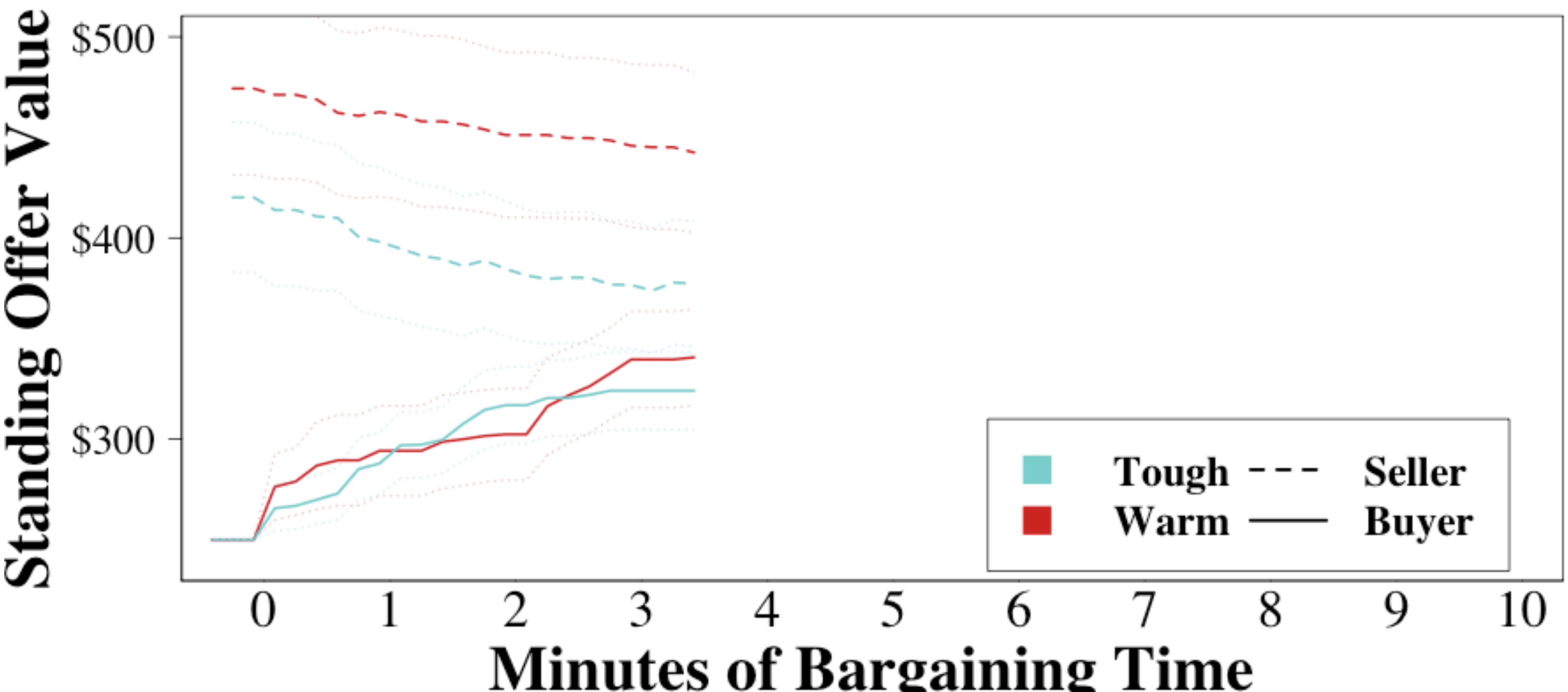


Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers earn worse final deals

- incentivized lab experiment with dyads
- driven by early seller concessions

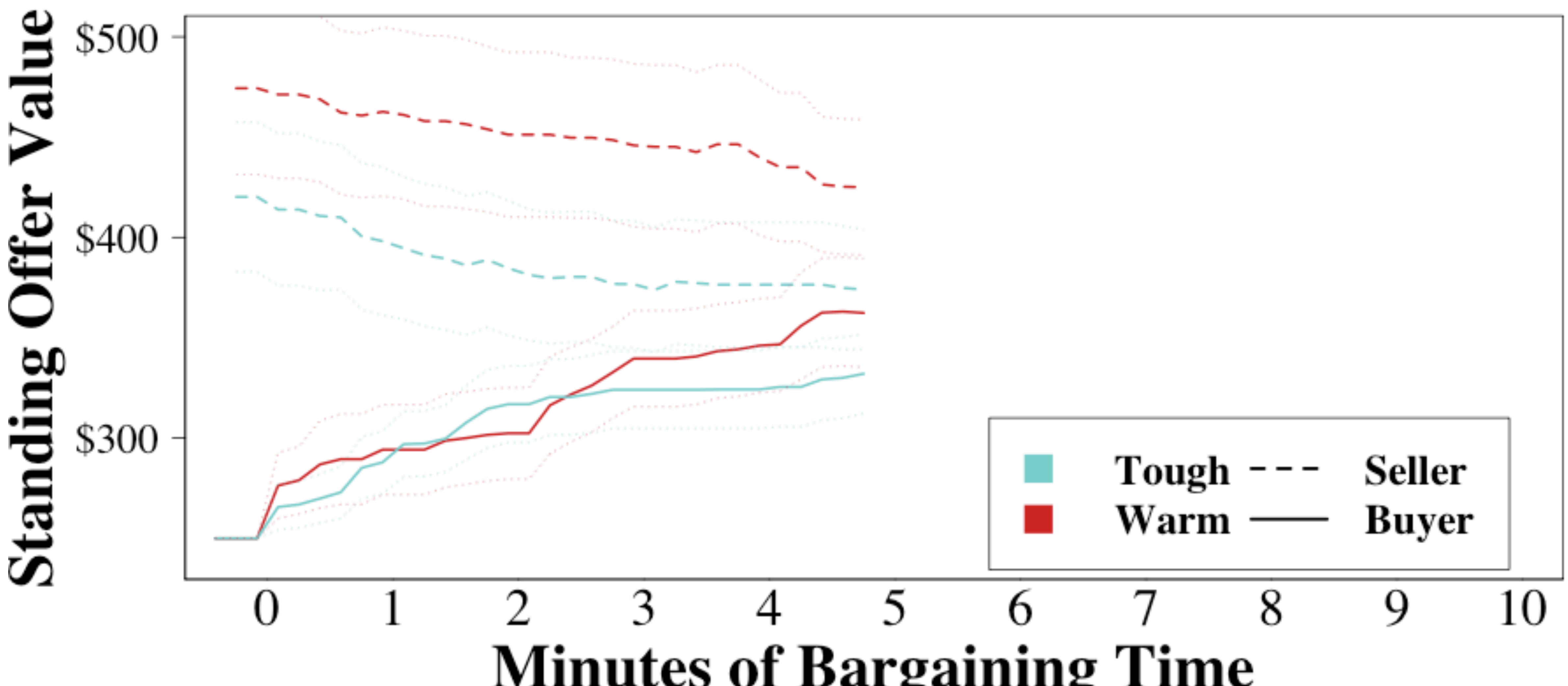


Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers earn worse final deals

- incentivized lab experiment with dyads
- driven by early seller concessions

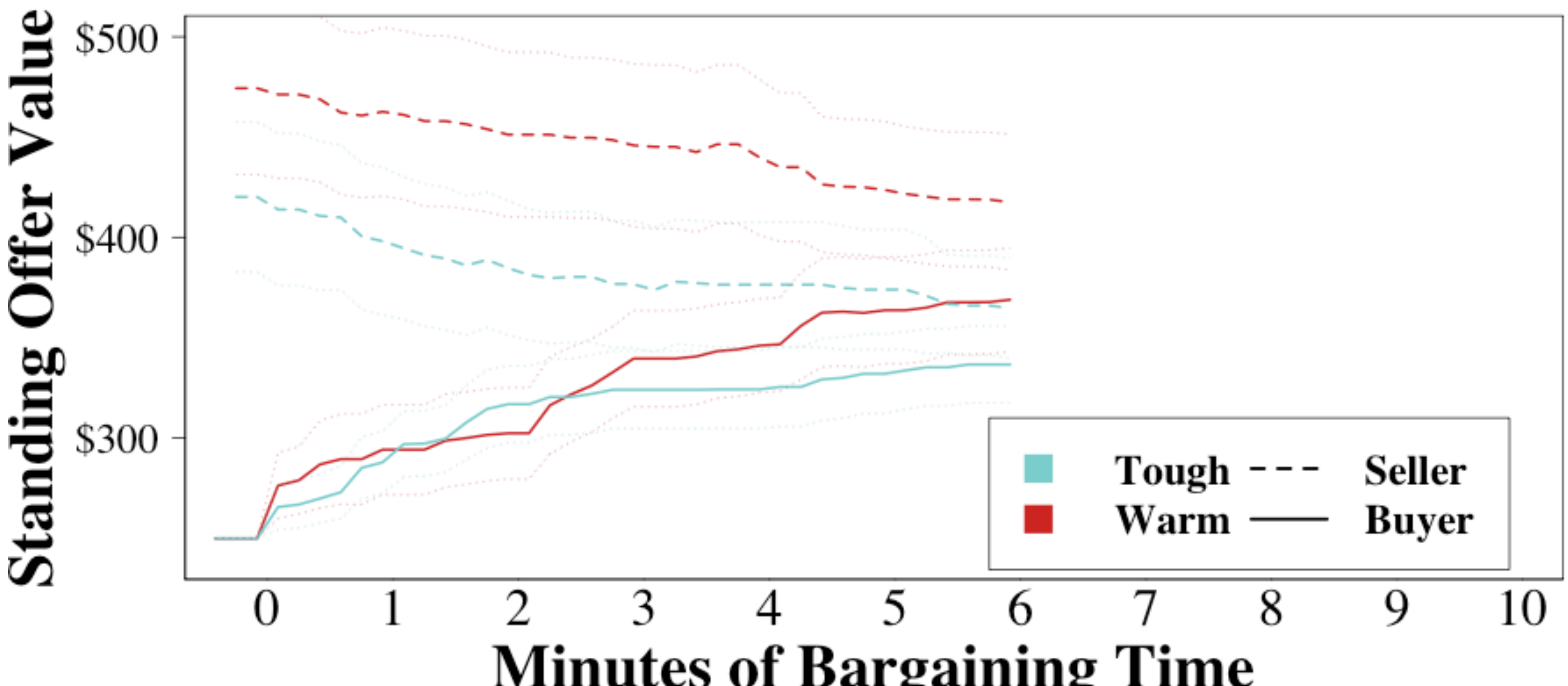


Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers earn worse final deals

- incentivized lab experiment with dyads
- driven by early seller concessions

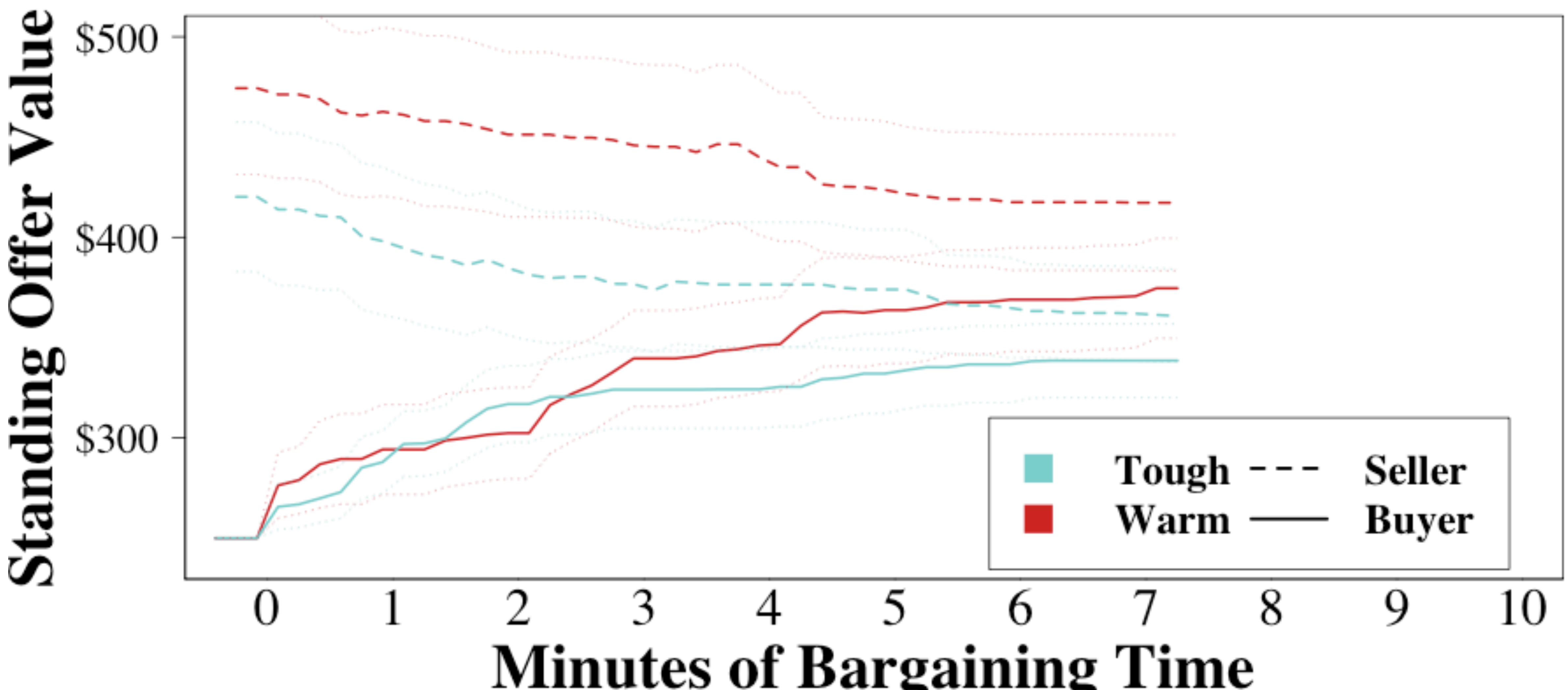


Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers earn worse final deals

- incentivized lab experiment with dyads
- driven by early seller concessions

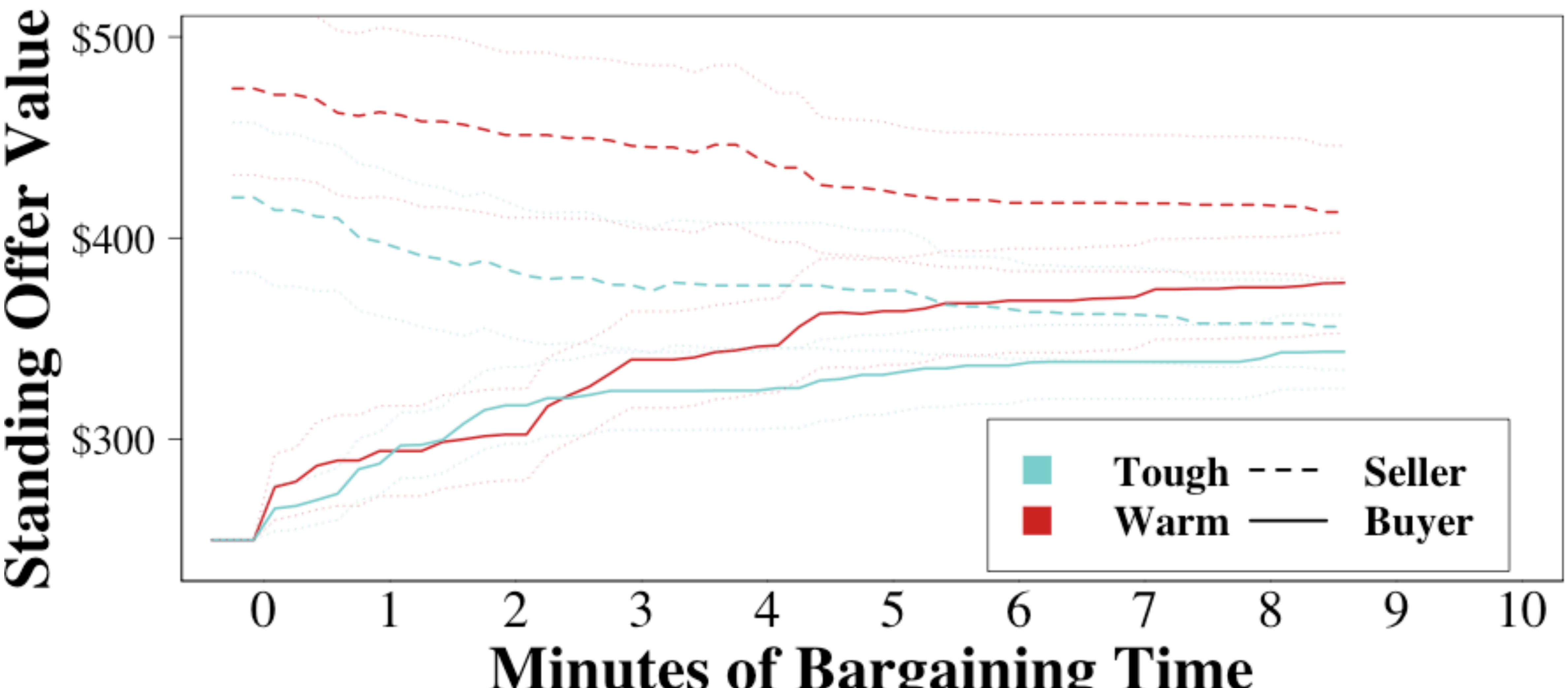


Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers earn worse final deals

- incentivized lab experiment with dyads
- driven by early seller concessions

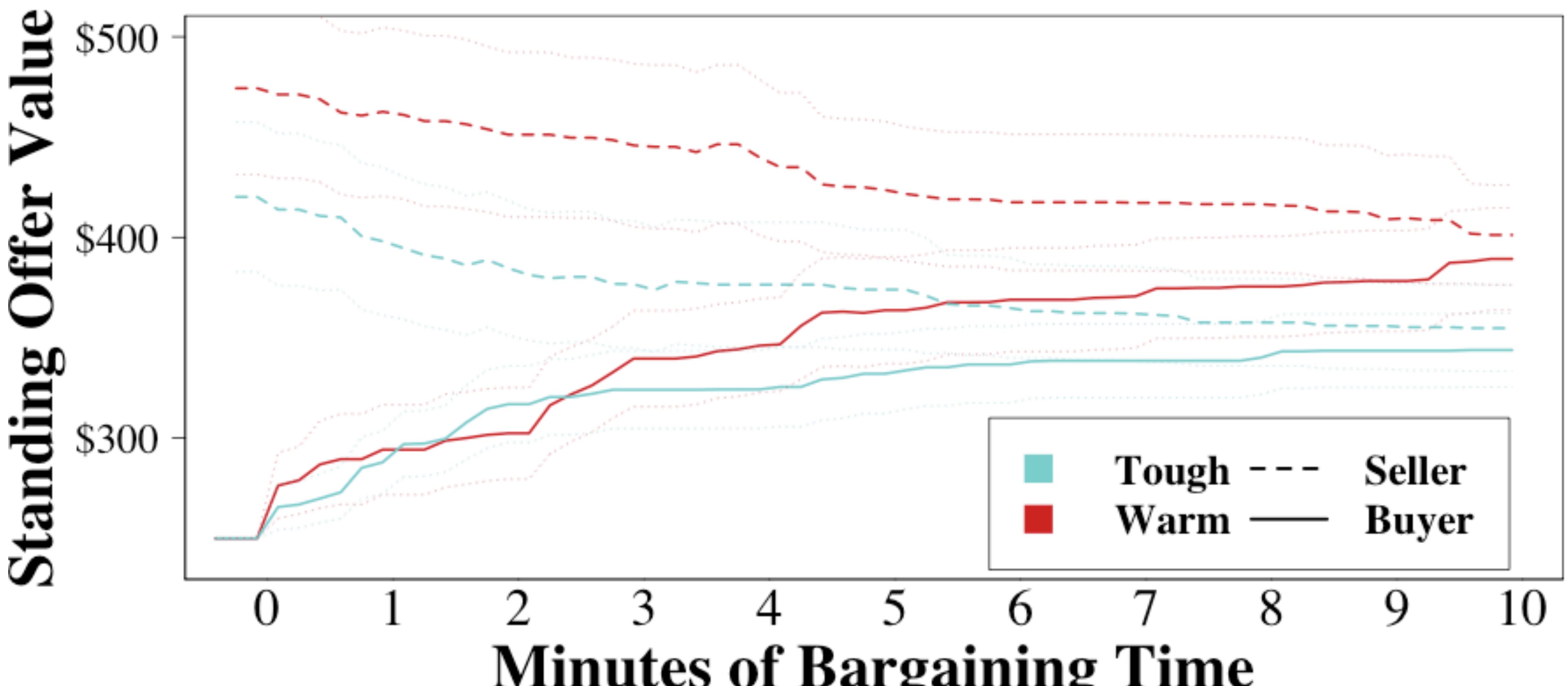


Communicating Warmth in …

(Jeong, Minson, Yeomans & Gino, 2018)

Warm offers earn worse final deals

- incentivized lab experiment with dyads
- driven by early seller concessions



How is Warmth Communicated?

How is Warmth Communicated?

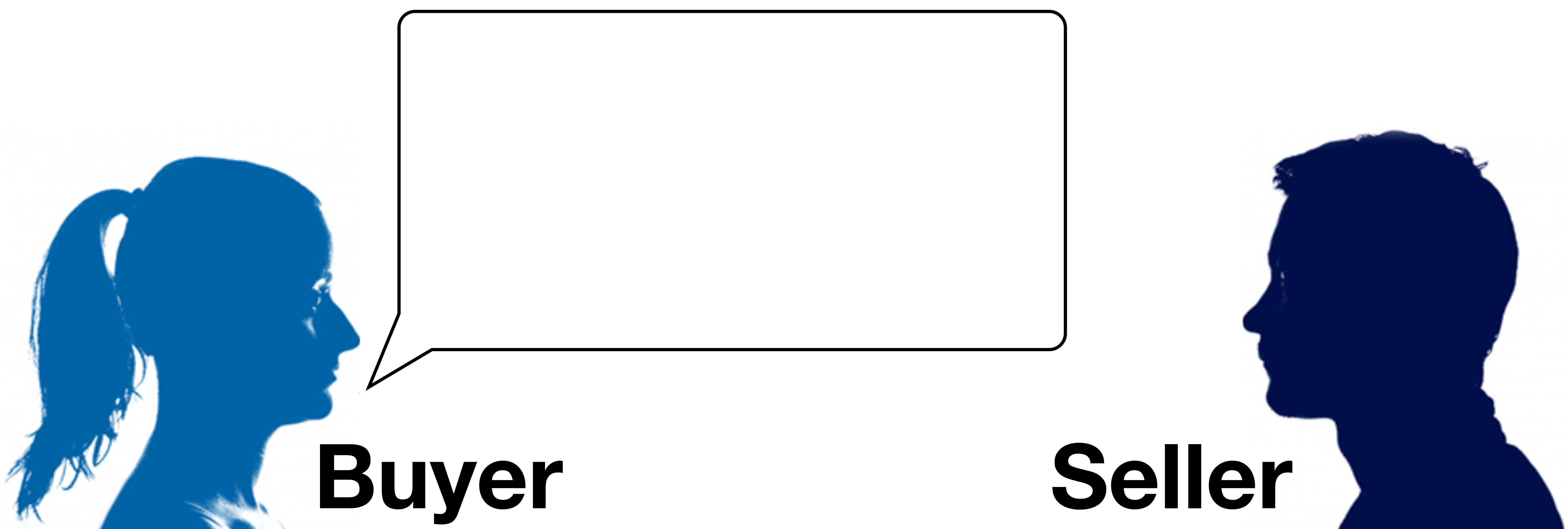
Buyer

How is Warmth Communicated?

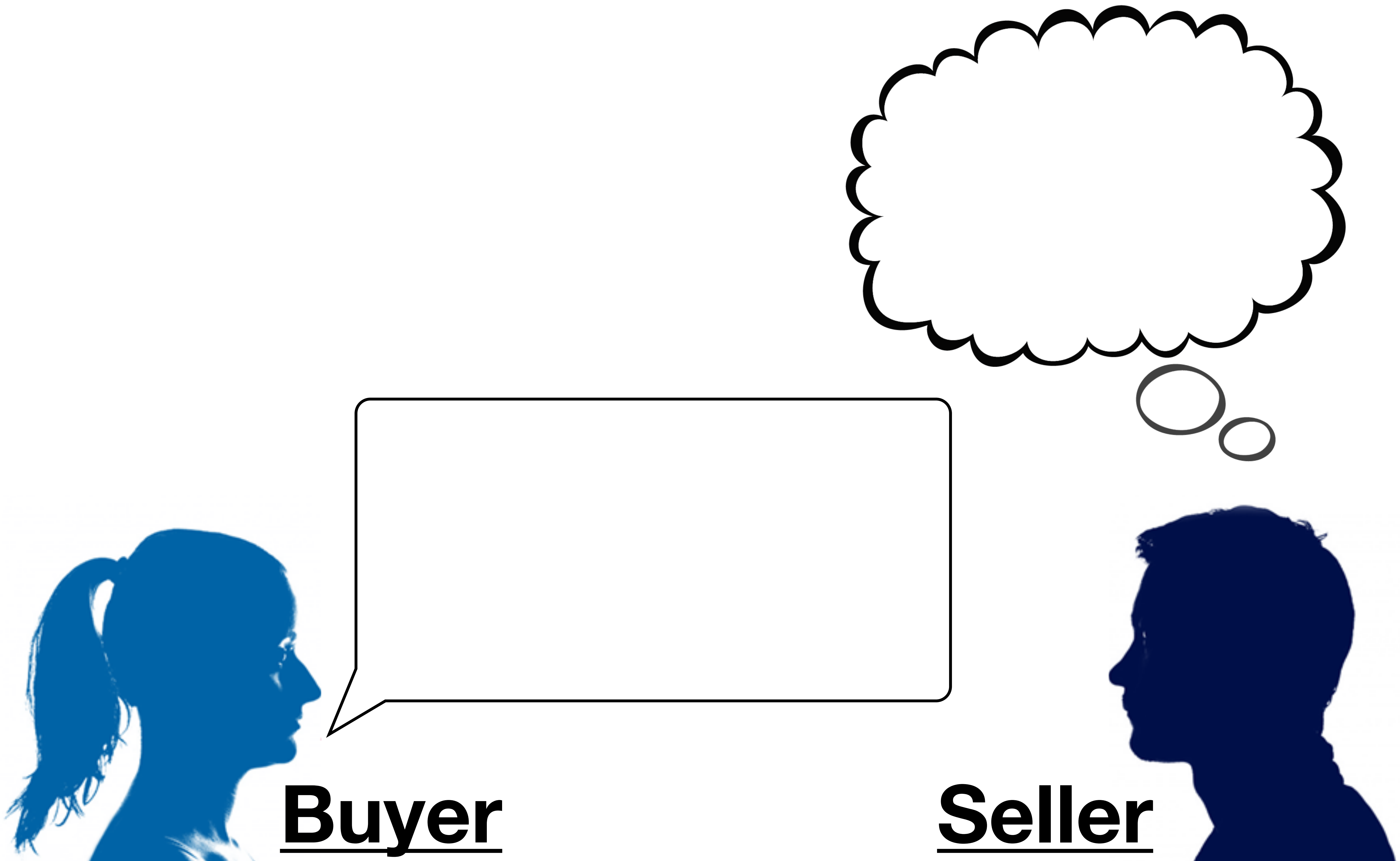
Buyer

Seller

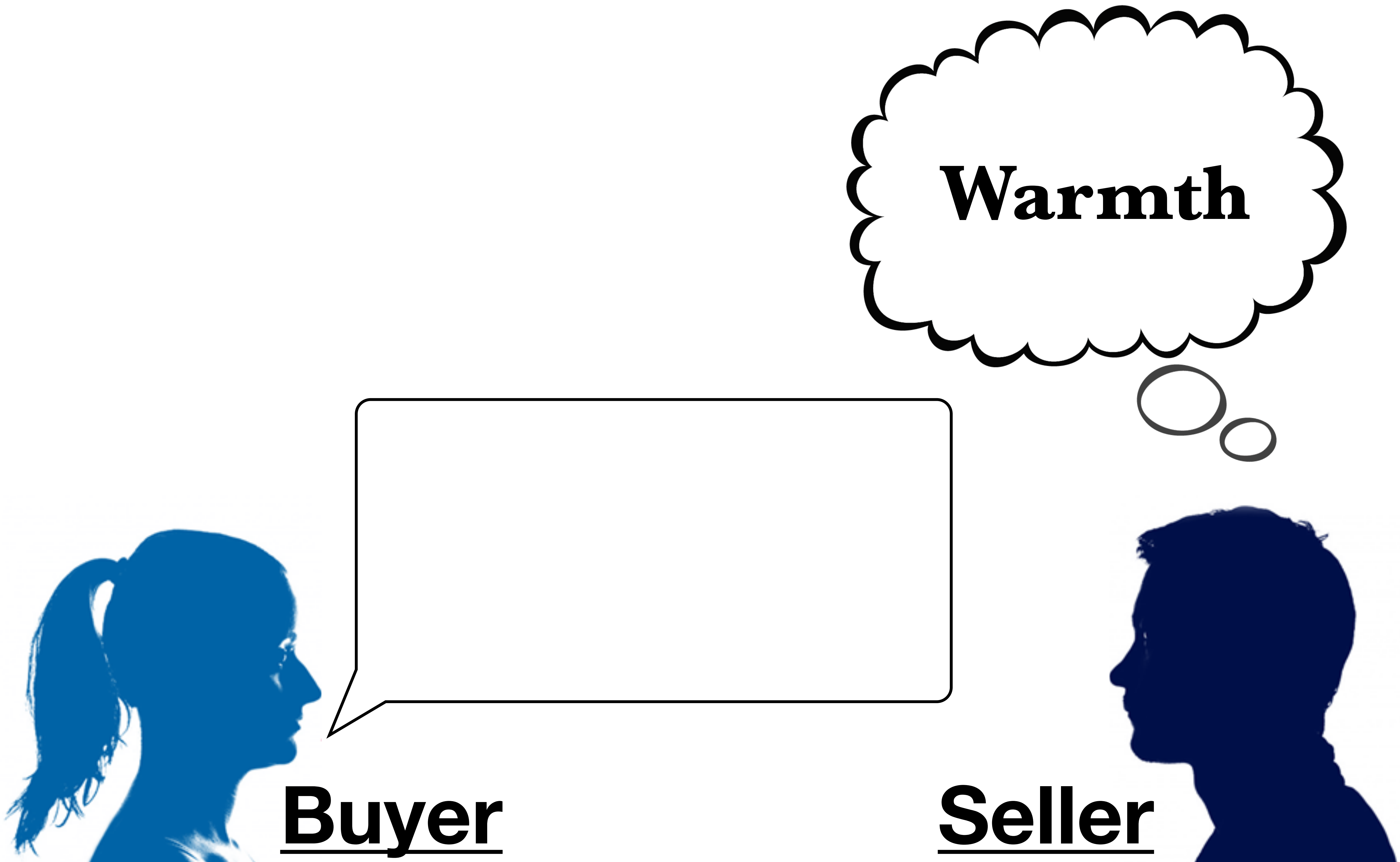
How is Warmth Communicated?



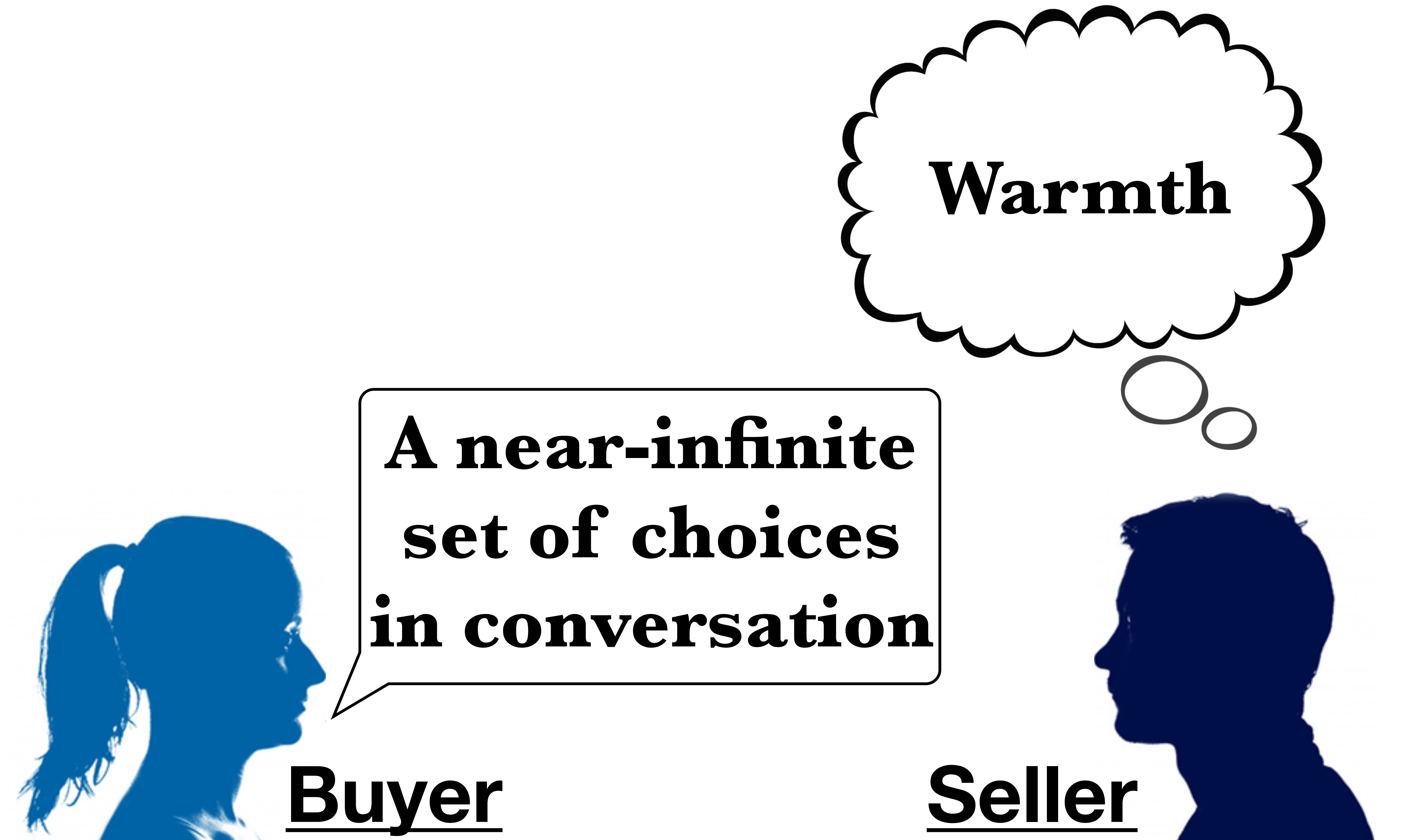
How is Warmth Communicated?



How is Warmth Communicated?



How is Warmth Communicated?



A Linguistic Model of Warmth

1. Collect negotiation transcripts

A Linguistic Model of Warmth

1. Collect negotiation transcripts

2. Randomly assign their negotiation strategy

A Linguistic Model of Warmth

1. Collect negotiation transcripts

2. Randomly assign their negotiation strategy

3. Train an algorithm to detect the strategy automatically

A Linguistic Model of Warmth

1. Collect negotiation transcripts

2. Randomly assign their negotiation strategy

3. Train an algorithm to detect the strategy automatically

We want to build an algorithm that is:

- scaleable

A Linguistic Model of Warmth

1. Collect negotiation transcripts

2. Randomly assign their negotiation strategy

3. Train an algorithm to detect the strategy automatically

We want to build an algorithm that is:
- scaleable
- interpretable

A Linguistic Model of Warmth

1. Collect negotiation transcripts

2. Randomly assign their negotiation strategy

3. Train an algorithm to detect the strategy automatically

We want to build an algorithm that is:

- scaleable
- interpretable
- valid

A Linguistic Model of Warmth

$$\hat{y} = a_0 \qquad\qquad\qquad\qquad\qquad\qquad + e$$

A Linguistic Model of Warmth

$$\hat{y} = a_0 + \quad x_1 + \quad x_2 + \quad x_3 + \ldots + e$$

Theory-Driven Feature Curation

Select set of observables ***x*** from literature

A Linguistic Model of Warmth

$$\hat{y} = a_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + e$$

Theory-Driven Feature Curation

Select set of observables ***x*** from literature

Empirical Feature Estimation

Determine **β** weights from ground-truth data

A Linguistic Model of Warmth

$$\hat{y} = a_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + e$$

Theory-Driven Feature Curation

Select set of observables ***x*** from literature

Empirical Feature Estimation

Determine **β** weights from ground-truth data

Actuarial Model of Politeness

(Meehl et al., 1954; Dawes, 1979; Grove et al., 1989)

A Linguistic Model of Warmth

$$\hat{y} = a_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + e$$

Theory-Driven Feature Curation

Select set of observables ***x*** from literature

Empirical Feature Estimation

Determine **β** weights from ground-truth data

Actuarial Model of Politeness

(Meehl et al., 1954; Dawes, 1979; Grove et al., 1989)

Markers of Politeness

Goffman, 1967; Lakoff, 1973; Brown & Levinson, 1987

Markers of Politeness

Goffman, 1967; Lakoff, 1973; Brown & Levinson, 1987

“universal dimension in human communication”

Markers of Politeness

Goffman, 1967; Lakoff, 1973; Brown & Levinson, 1987

Positive Politeness

Markers of Politeness

Goffman, 1967; Lakoff, 1973; Brown & Levinson, 1987

Positive Politeness

Bolstering listener's self-image

Markers of Politeness

Goffman, 1967; Lakoff, 1973; Brown & Levinson, 1987

Positive Politeness

Bolstering listener's self-image

+ Gratitude
+ Complements
+ Open-ended Questions
+ In-Group Identity
+ Formal Titles
- Informal Titles

Markers of Politeness

Goffman, 1967; Lakoff, 1973; Brown & Levinson, 1987

Positive Politeness

Bolstering listener's self-image

+ Gratitude
+ Complements
+ Open-ended Questions
+ In-Group Identity
+ Formal Titles
- Informal Titles

Negative Politeness

Upholding listener's autonomy

Markers of Politeness

Goffman, 1967; Lakoff, 1973; Brown & Levinson, 1987

Positive Politeness

Bolstering listener's self-image

- \+ Gratitude
- \+ Complements
- \+ Open-ended Questions
- \+ In-Group Identity
- \+ Formal Titles
- \- Informal Titles

Negative Politeness

Upholding listener's autonomy

- \+ Minimizing
- \+ Indirect requests
- \+ Apologies
- \+ Hedging
- \- Negations
- \- Bare Commands

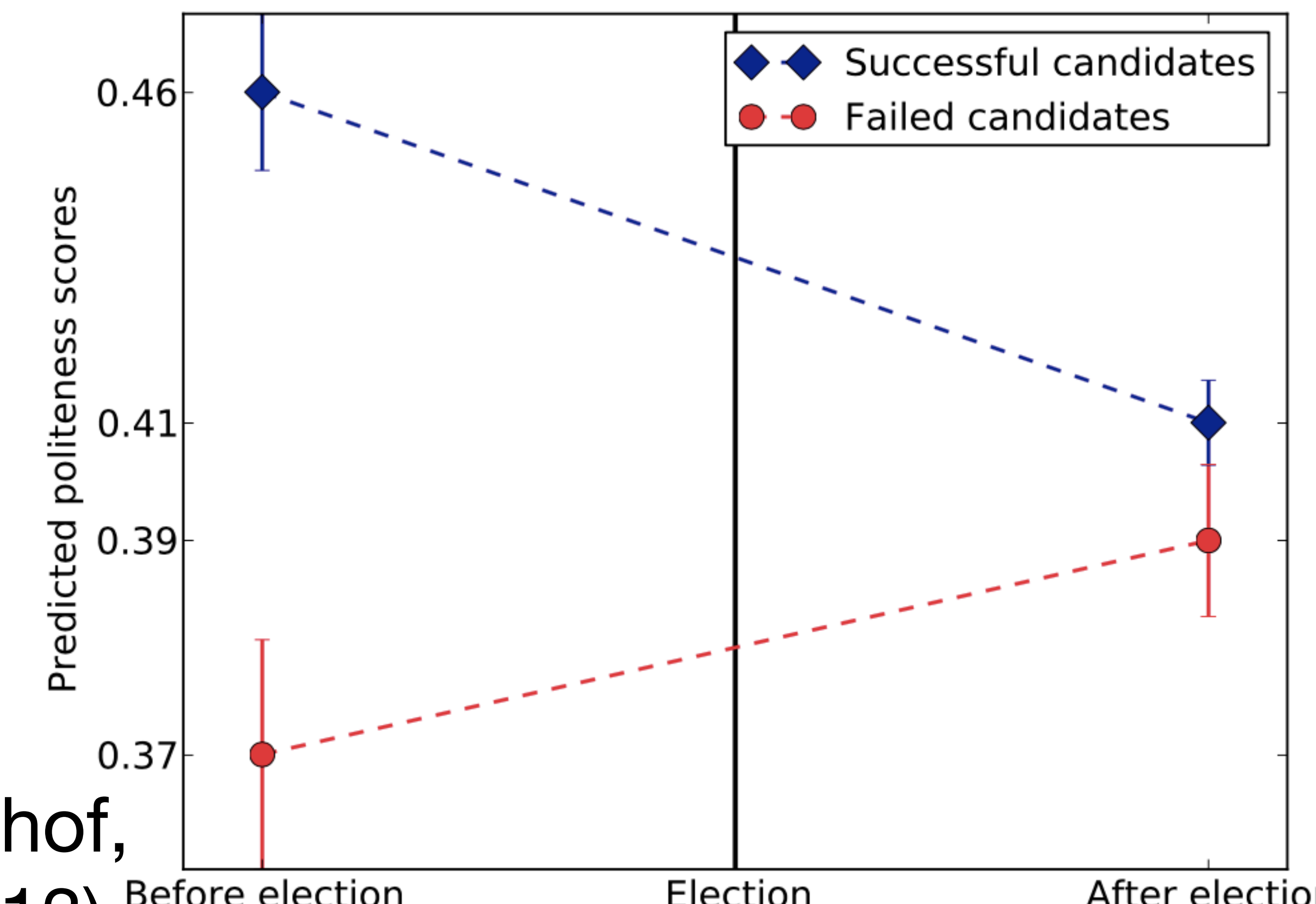
Markers of Politeness

A Computational Approach to Politeness with Applications to Social Factors

(Danescu-Niculescu-Mizil, Sudhof, Jurafsky, Leskovec & Potts, 2013)

Markers of Politeness

A Computational Approach to Politeness with Applications to Social Factors



(Danescu-Niculescu-Mizil, Sudhof, Jurafsky, Leskovec & Potts, 2013)

Markers of Politeness

Language from Police Body Camera Footage shows Racial Disparities in Officer Respect

(Voigt, Camp, Prabakharan, Hamilton, Hetey, Griffiths, Jurgens, Jurafsky & Eberhart, 2017)

Markers of Politeness

Language from Police Body Camera Footage shows Racial Disparities in Officer Respect

(Voigt, Camp, Prabakharan, Hamilton, Hetey, Griffiths, Jurgens, Jurafsky & Eberhart, 2017)

Markers of Politeness

Apologies

Markers of Politeness

Apologies

"I apologize for my behavior"

Markers of Politeness

Apologies

"I apologize for my behavior"

"I apologise for my behaviour"

Markers of Politeness

Apologies

"I apologize for my behavior"

"I apologise for my behaviour"

"Not until you apologise for your behaviour"

Markers of Politeness

Apologies

"I apologize for my behavior"

"I apologise for my behaviour"

"Not until you apologise for your behaviour"

"I sincerely apologise for my behaviour"

Dependency Trees

I sincerely apologise for my behaviour

Dependency Trees

I sincerely apologise for my behaviour

PRON ADV VERB ADP DET NOUN

Dependency Trees

The "root"

I sincerely apologise for my behaviour

PRON ADV VERB ADP DET NOUN

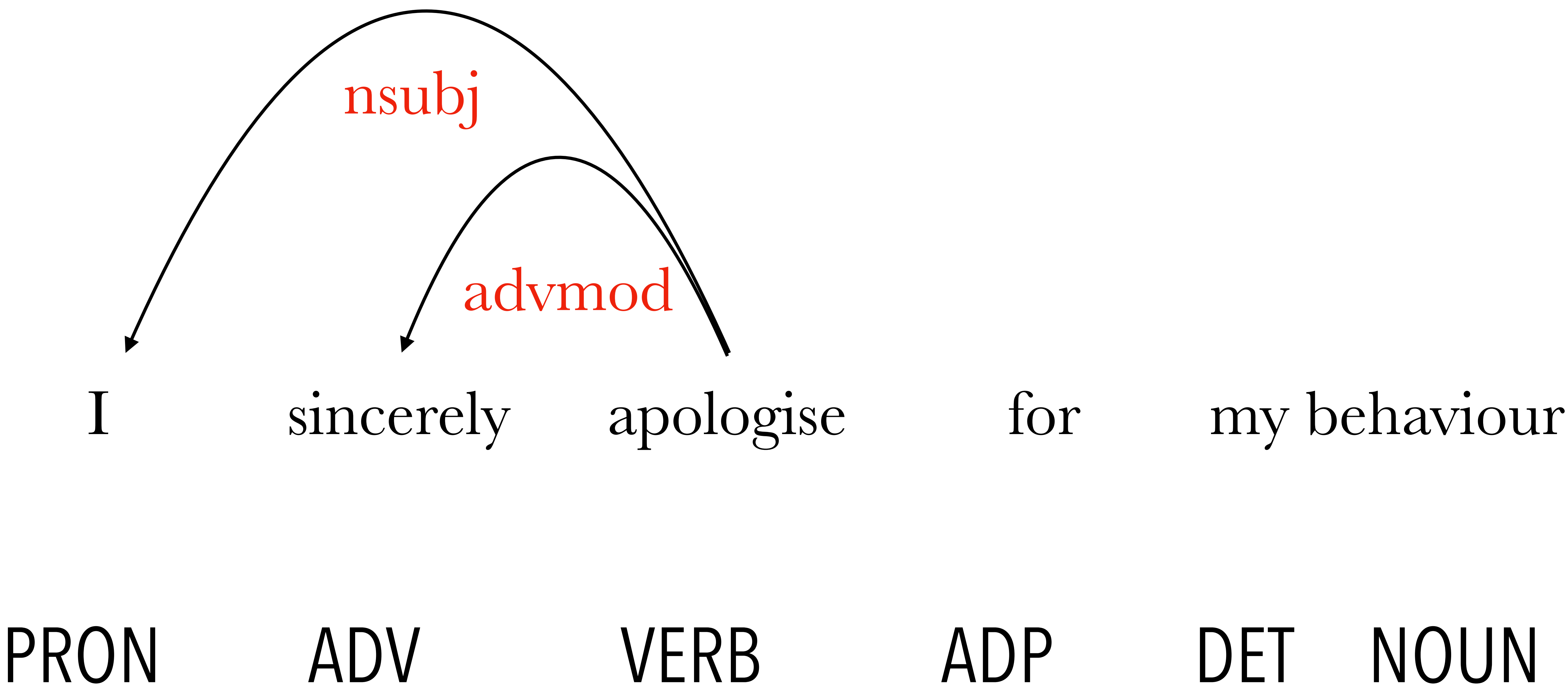
Dependency Trees

nsubj

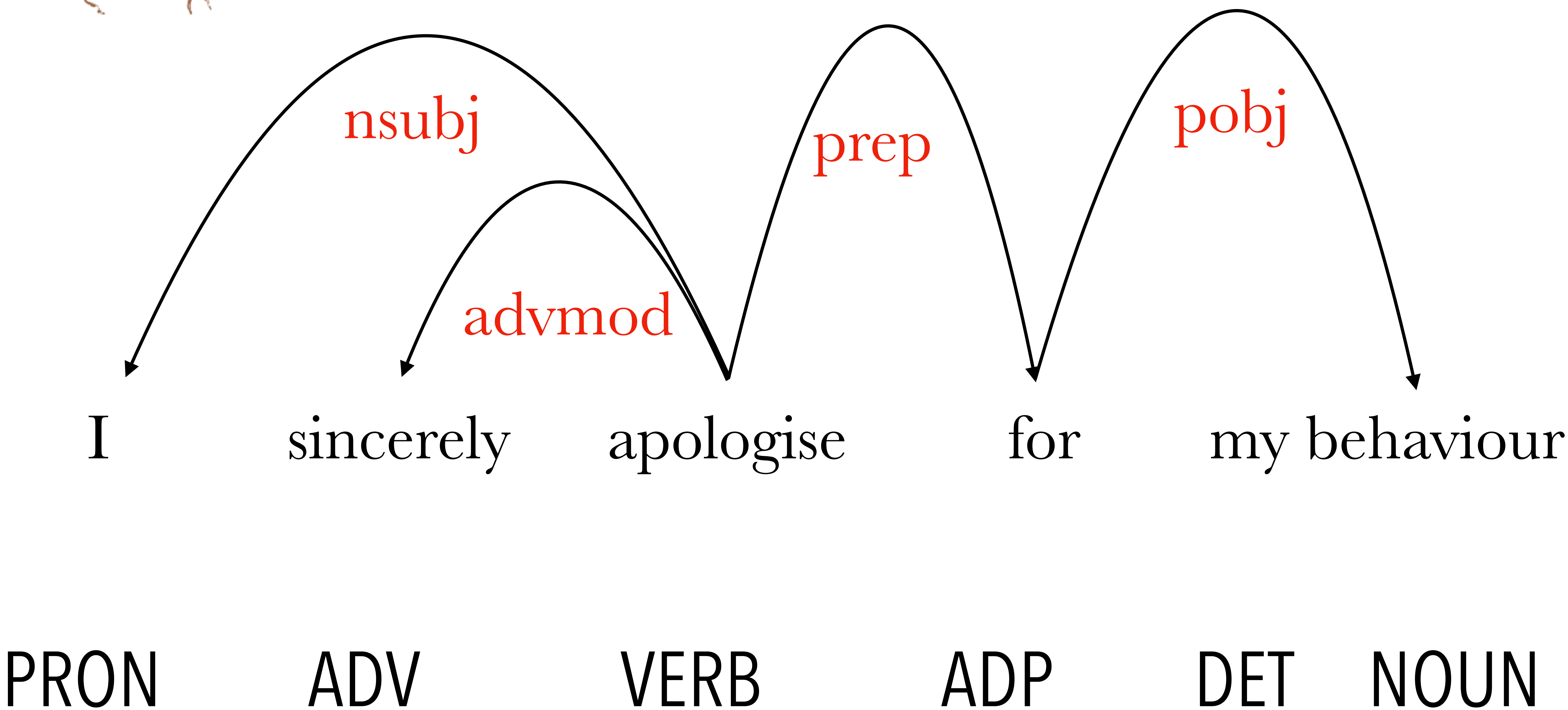
I sincerely apologise for my behaviour

PRON ADV VERB ADP DET NOUN

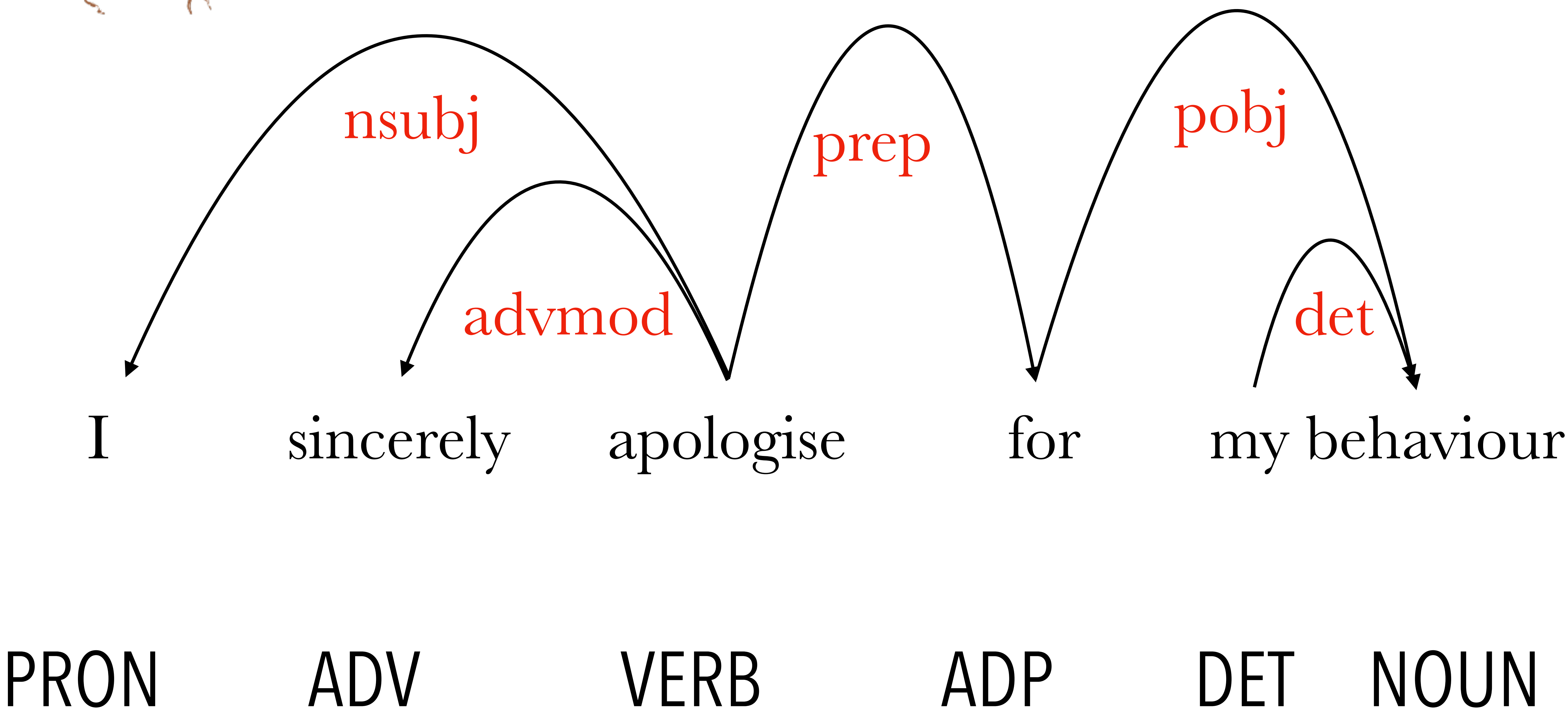
Dependency Trees



Dependency Trees



Dependency Trees



Dependency Trees

	Word
1	I
2	sincerely
3	apologise
4	for
5	my
6	behaviour

Dependency Trees

	Word
1	I
2	sincerely
3	apologise
4	for
5	my
6	behaviour

Dependency Trees

spaCy

	Word	Part of Speech	Head	Relation	Dependency Pair
1	I	PRON	3	nsubj	nsubj(apologize, I)
2	sincerely	ADV	3	advmod	advmod(apologize, sincerely)
3	apologise	VERB	3	ROOT	ROOT(--,apologise)
4	for	ADP	3	prep	prep(apologise,for)
5	my	DET	6	poss	det(behaviour, my)
6	behaviour	NOUN	4	pobj	pobj(for, behaviour)

Dependency Trees

	Word	Part of Speech	Head	Relation	Dependency Pair
1	I	PRON	3	nsubj	**nsubj(apologize, I)**
2	sincerely	ADV	3	advmod	advmod(apologize, sincerely)
3	apologise	VERB	3	ROOT	ROOT(--,apologise)
4	for	ADP	3	prep	prep(apologise,for)
5	my	DET	6	poss	det(behaviour, my)
6	behaviour	NOUN	4	pobj	pobj(for, behaviour)

Dependency Trees

Dependency Trees

But why though?

Dependency Trees

But why though?

The actual structure of communication

Dependency Trees

But why though?

The actual structure of communication

Word order matters!

"I don't understand you" vs. "I understand you don't"

Dependency Trees

But why though?

The actual structure of communication

Word order matters!

"I don't understand you" vs. "I understand you don't"

Not in LIWC, dictionaries, word2vec...

Dependency Trees

But why though?

The actual structure of communication

Word order matters!

"I don't understand you" vs. "I understand you don't"

Not in LIWC, dictionaries, word2vec...

What about neural nets? (BERT, GPT-3...)

Emergent linguistic structure in artificial neural networks trained by self-supervision

Christopher D. Manning[a,1], Kevin Clark[a], John Hewitt[a], Urvashi Khandelwal[a], and Omer Levy[b]

[a]Computer Science Department, Stanford University, Stanford, CA 94305; and [b]Facebook Artificial Intelligence Research, Facebook Inc., Seattle, WA 98109

Edited by Matan Gavish, Hebrew University of Jerusalem, Jerusalem, Israel, and accepted by Editorial Board Member David L. Donoho April 13, 2020 (received for review June 3, 2019)

This paper explores the knowledge of linguistic structure learned by large artificial neural networks, trained via self-supervision, whereby the model simply tries to predict a masked word in a given context. Human language communication is via sequences of words, but language understanding requires constructing rich hierarchical structures that are never observed explicitly. The mechanisms for this have been a prime mystery of human language acquisition, while engineering work has mainly proceeded by supervised learning on treebanks of sentences hand labeled for this latent structure. However, we demonstrate that modern deep contextual language models learn major aspects of this structure, without any explicit supervision. We develop methods for identifying linguistic hierarchical structure emergent in artificial neural networks and demonstrate that components in these models focus on syntactic grammatical relationships and anaphoric coreference. Indeed, we show that a linear transformation of learned embeddings in these models captures parse tree distances to a surprising degree, allowing approximate reconstruction of the sentence tree structures normally assumed by linguists. These results help explain why these models have brought such large improvements across many language-understanding tasks.

own supervised learning problems by choosing to interpret some of the data as a "label" to be predicted.† The canonical case for human language is the language-modeling task of trying to predict the next word in an utterance based on the temporally preceding words (Fig. 2). Variant tasks include the masked language-modeling task of predicting a masked word in a text [a.k.a. the cloze task (11)] and predicting the words likely to occur around a given word (12, 13). Autoencoders (14) can also be thought of as self-supervised learning systems. Since no explicit labeling of the data is required, self-supervised learning is a type of unsupervised learning, but the approach of self-generating supervised learning objectives differentiates it from other unsupervised learning techniques such as clustering.

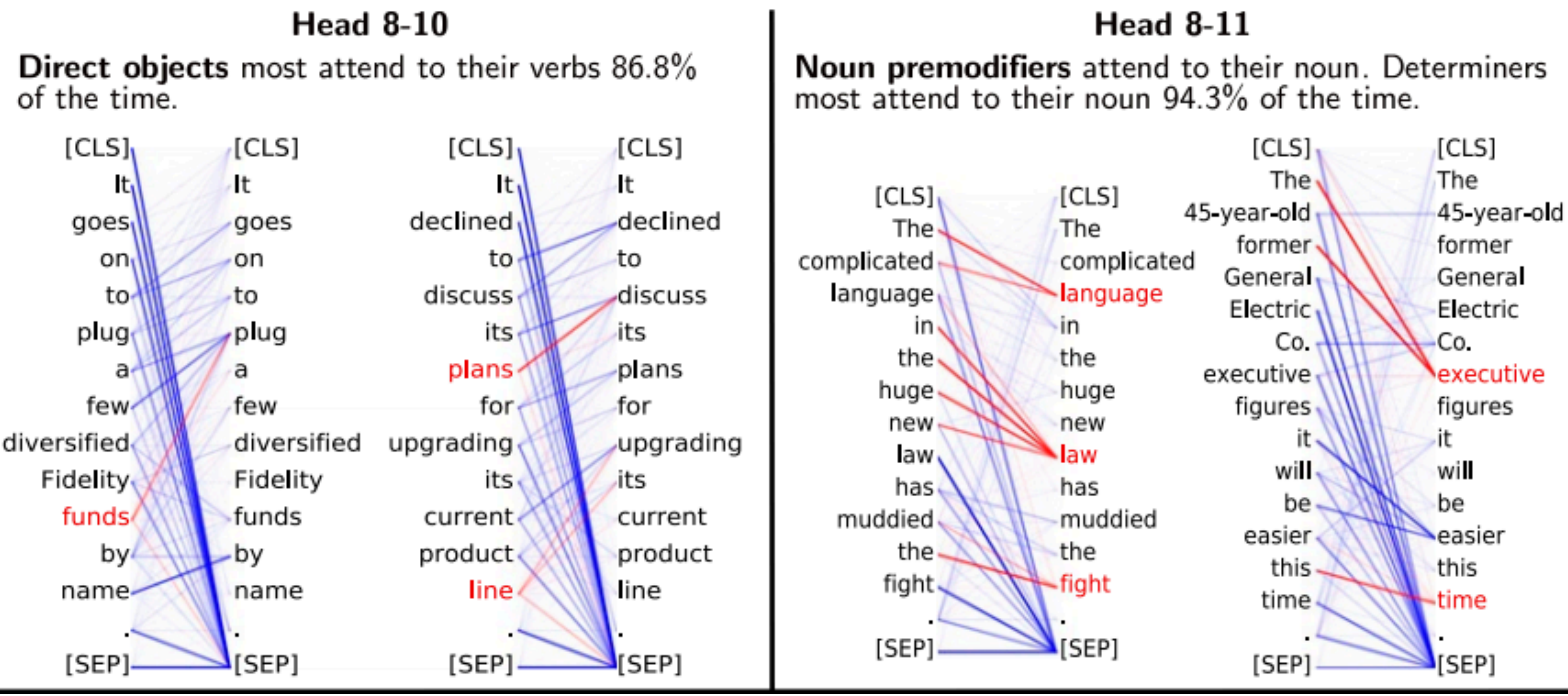
One might expect that a machine-learning model trained to predict the next word in a text will just be a giant associational learning machine, with lots of statistics on how often the word restaurant is followed by kitchen and perhaps some basic abstracted sequence knowledge such as knowing that adjectives are commonly followed by nouns in English. It is not at all clear that such a system can develop interesting knowledge of the linguistic structure of whatever human language the system is trained on. Indeed, this has been the dominant perspective in linguistics, where language models have long been seen as inadequate

Emergent linguistic structure in artificial neural networks trained by self-supervision

Christopher D. Manning[a,1], **Kevin Clark**[a], **John Hewitt**[a], **Urvashi Khandelwal**[a], **and Omer Levy**[b]

[a]Computer Science Department, Stanford University, Stanford, CA 94305; and [b]Facebook Artificial Intelligence Research, Facebook Inc., Seattle, WA 98109

Edited by Matan Gavish, Hebrew University of Jerusalem, Jerusalem, Israel, and accepted by Editorial Board Member David L. Donoho April 13, 2020



A Linguistic Model of Warmth

$$\hat{y} = a_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + e$$

Theory-Driven Feature Curation

Select set of observables ***x*** from literature

Empirical Feature Estimation

Determine **β** weights from ground-truth data

Actuarial Model of Politeness

(Meehl et al., 1954; Dawes, 1979; Grove et al., 1989)

A Linguistic Model of Warmth

$$\hat{y} = a_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + e$$

Theory-Driven Feature Curation

Select set of observables ***x*** from literature

Empirical Feature Estimation

Determine **β** weights from ground-truth data

Actuarial Model of Politeness

(Meehl et al., 1954; Dawes, 1979; Grove et al., 1989)

Communicating Warmth in …

Communicating Warmth in …

mTurkers can write phone offers! (n = 355)

Communicating Warmth in …

mTurkers can write phone offers! (n = 355)

- encouragement design - tough vs. warm instructions
- “ground truth” is treatment effect

Communicating Warmth in …

mTurkers can write phone offers! (n = 355)

- encouragement design - tough vs. warm instructions
- “ground truth” is treatment effect

Message	Condition
Hi, since this is a...	0
Hi, I saw your ad...	1
Hey, I hope you are...	1
Hi, I am interested...	0
Hi, I am interested...	0
I saw your add on...	0

Communicating Warmth in …

Communicating Warmth in …

mTurkers can write phone offers! (n = 355)

- encouragement design - tough vs. warm instructions
- “ground truth” is treatment effect

Message	Condition
Hi, since this is a...	0
Hi, I saw your ad...	1
Hey, I hope you are...	1
Hi, I am interested...	0
Hi, I am interested...	0
I saw your add on...	0

Communicating Warmth in …

mTurkers can write phone offers! (n = 355)

- encouragement design - tough vs. warm instructions
- "ground truth" is treatment effect

Message	**Condition**
Hi, since this is a...	0
Hi, I saw your ad...	1
Hey, I hope you are...	1
Hi, I am interested...	0
Hi, I am interested...	0
I saw your add on...	0

We want to build an algorithm that is:

- interpretable
- valid
- scaleable

Communicating Warmth in …

mTurkers can write phone offers! (n = 355)

- encouragement design - tough vs. warm instructions
- "ground truth" is treatment effect

Message	Condition
Hi, since this is a...	0
Hi, I saw your ad...	1
Hey, I hope you are...	1
Hi, I am interested...	0
Hi, I am interested...	0
I saw your add on...	0

We want to build an algorithm that is:

- **interpretable**
- valid
- scaleable

Communicating Warmth in …

mTurkers can write phone offers! (n = 355)

- encouragement design - tough vs. warm instructions
- “ground truth” is treatment effect

Hello, I am interested in purchasing this phone for work purposes but unfortunately have a spending limit of $115 per my company's budget. Is there any way that you would be willing to work with me on this? I really appreciate your time and consideration.   Thank You, Ashleigh.

Communicating Warmth in …

mTurkers can write phone offers! (n = 355)

- encouragement design - tough vs. warm instructions
- “ground truth” is treatment effect

Hello, Hope you are doing well. I recently saw your posting for the iPhone 6 Plus for sale and I am interested. I would love to come by and buy it from you today. I can pay you in cash. Would you be willing to sell it to me for $115 paid in cash today? Thanks so much. I really appreciate it.

Communicating Warmth in …

mTurkers can write phone offers! (n = 355)

- encouragement design - tough vs. warm instructions
- “ground truth” is treatment effect

Come on. The price you are offering on a product that ISN'T NEW is unreasonable. Now, I for one am very interested in getting this item. BUT, I will only pay $115. I am not paying a penny more.

Communicating Warmth in …

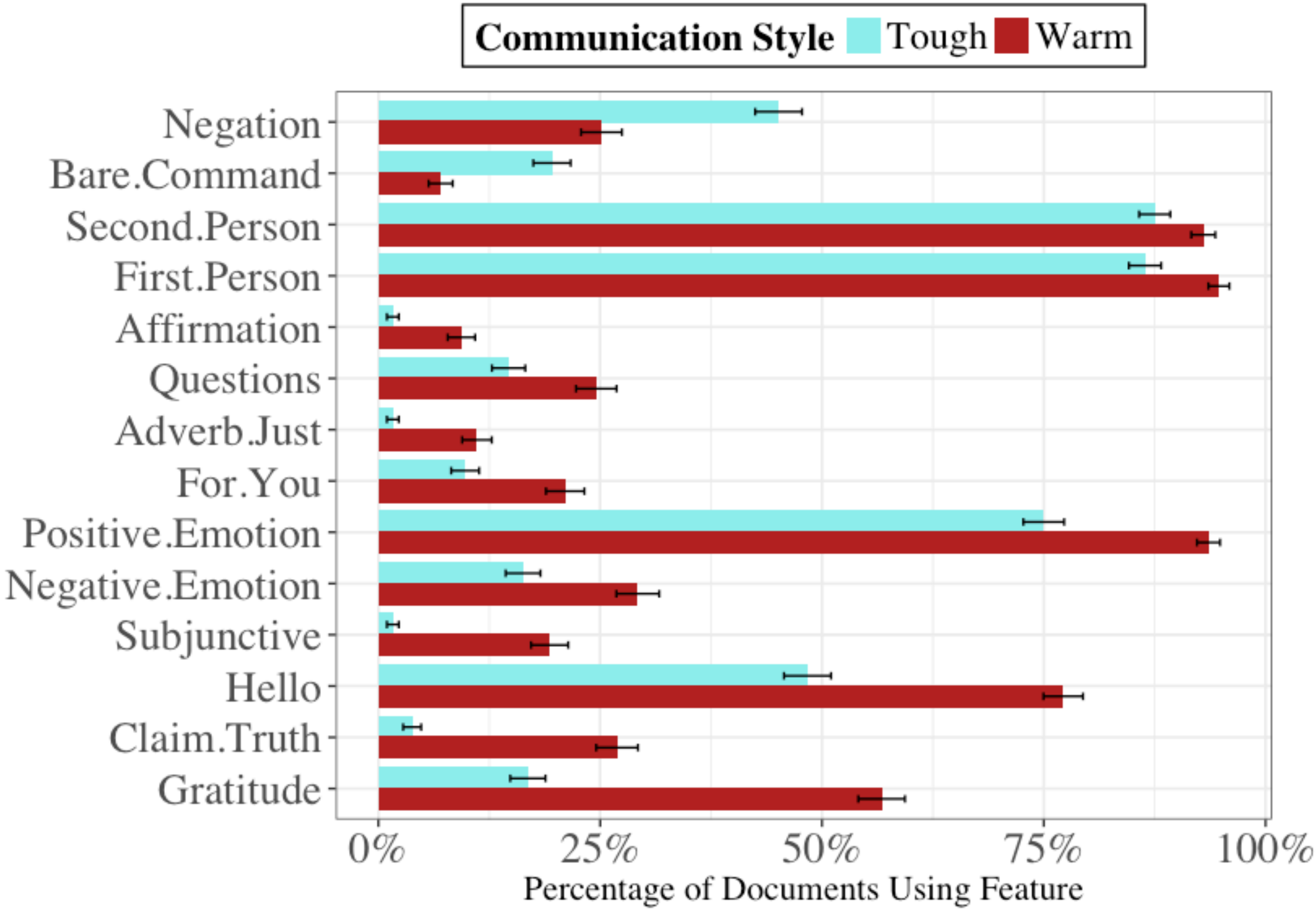
mTurkers can write phone offers! (n = 355)

- encouragement design - tough vs. warm instructions
- “ground truth” is treatment effect

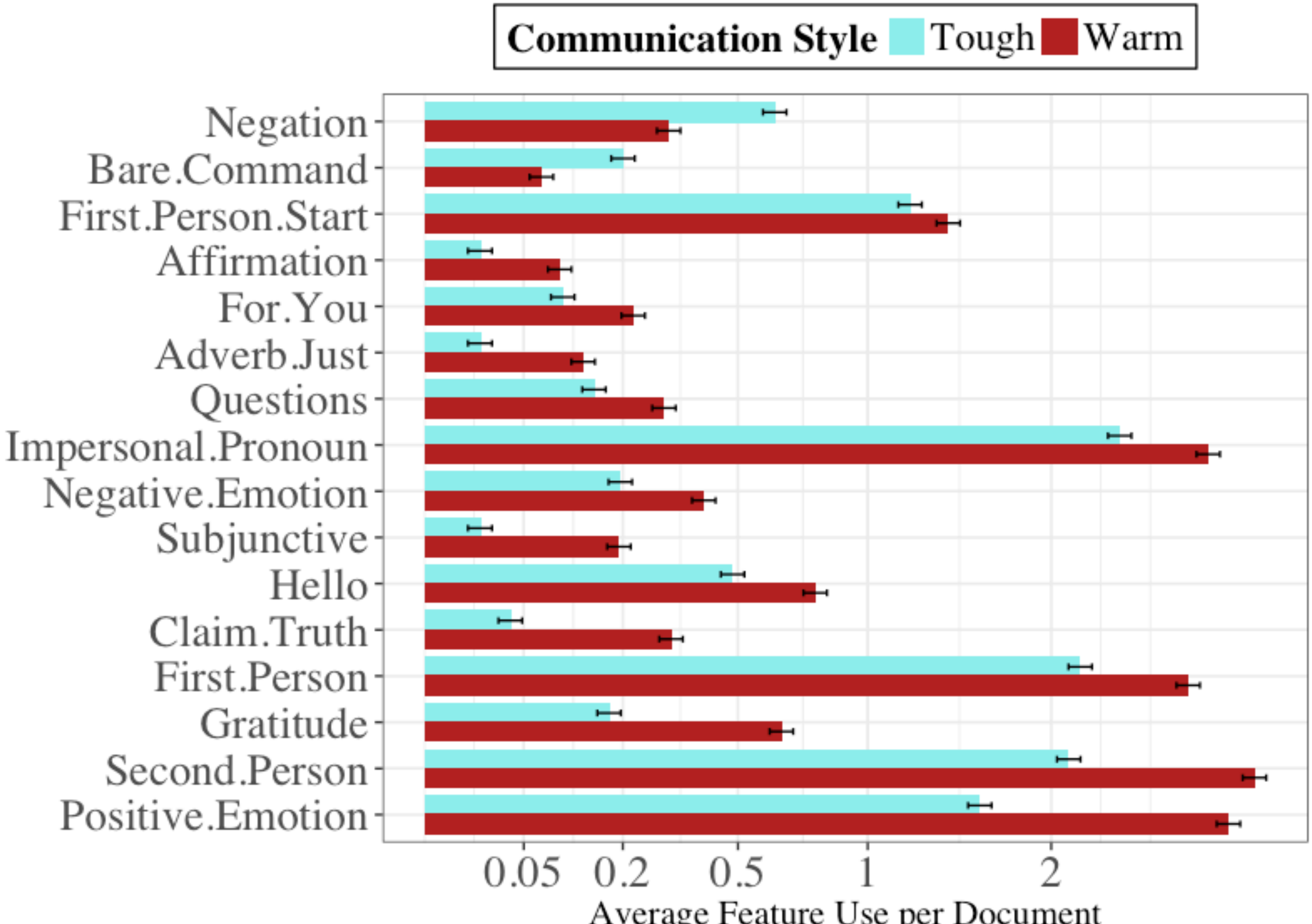
I will buy the phone as is for $115. I don't want to pay more than the amount that I stated. If you accept my price please contact me within 24 hours. If I don't hear from you in the next 24 hours I will take it that you will accept my price.

Communicating Warmth in …

Communicating Warmth in …



Communicating Warmth in …



Communicating Warmth in …

mTurkers can write phone offers! (n = 355)

- encouragement design - tough vs. warm instructions
- “ground truth” is treatment effect

Message	Condition
Hi, since this is a...	0
Hi, I saw your ad...	1
Hey, I hope you are...	1
Hi, I am interested...	0
Hi, I am interested...	0
I saw your add on...	0

We want to build an algorithm that is:

- interpretable

- **valid**

- scaleable

Machine Learning (briefly)

Machine Learning (briefly)

Building a Prediction Model

- key insight: "regularization"
- slightly fancier than a multiple regression

(see Tibshirani, 1996; Friedman, Hastie & Tibshirani, 2010)

Machine Learning (briefly)

$$\min_{\beta \in \mathbb{R}^p} \left\{ \frac{1}{N} ||y - X\beta||_2^2 + \lambda ||\beta||_1 \right\}$$

Machine Learning (briefly)

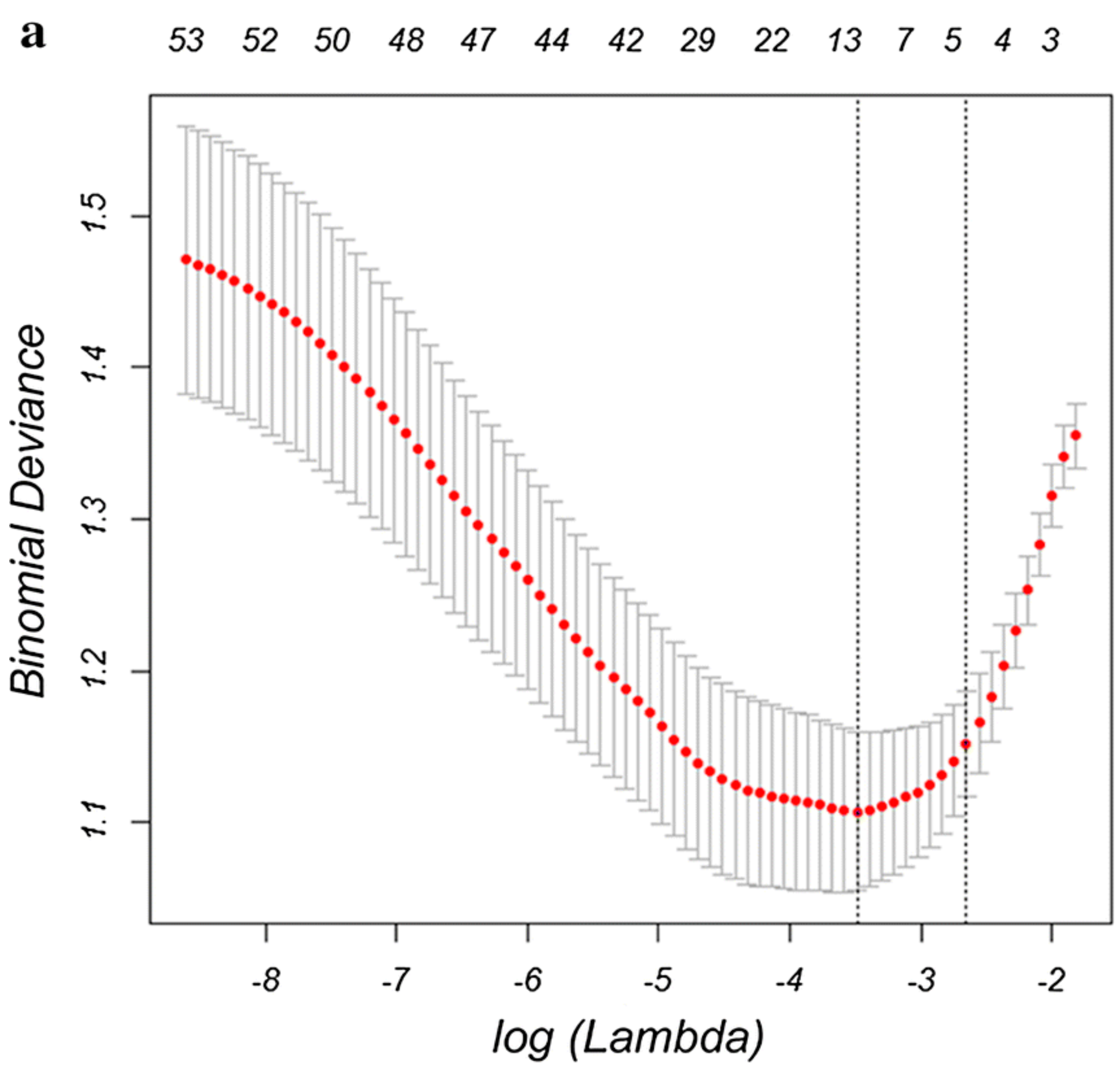
$$\min_{\beta \in \mathbb{R}^p} \left\{ \frac{1}{N} \|y - X\beta\|_2^2 + \lambda \|\beta\|_1 \right\}$$

Machine Learning (briefly)

$$\min_{\beta \in \mathbb{R}^p} \left\{ \frac{1}{N} ||y - X\beta||_2^2 + \lambda ||\beta||_1 \right\}$$

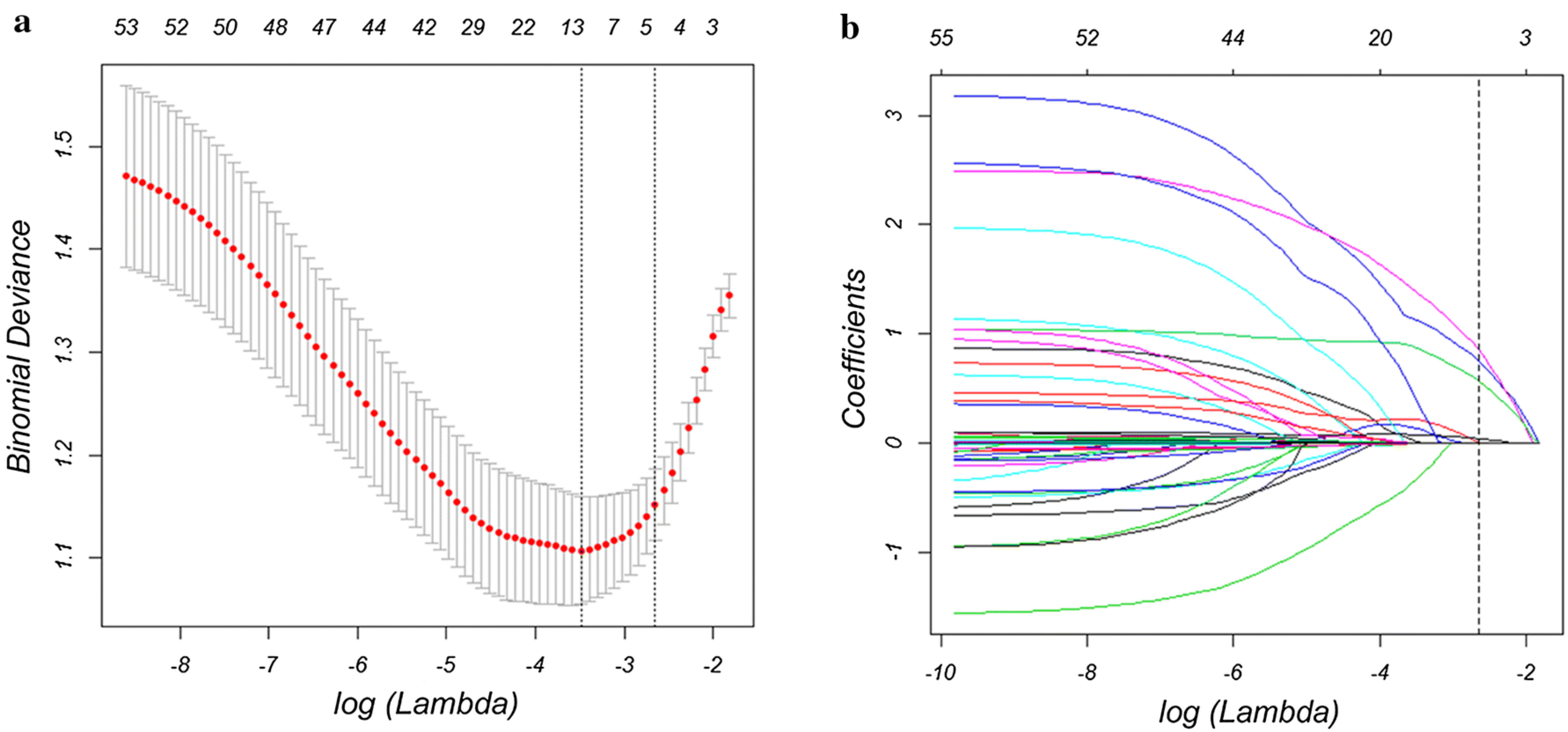
Machine Learning (briefly)

$$\min_{\beta \in \mathbb{R}^p} \left\{ \frac{1}{N} \|y - X\beta\|_2^2 + \lambda \|\beta\|_1 \right\}$$



Machine Learning (briefly)

$$\min_{\beta \in \mathbb{R}^p} \left\{ \frac{1}{N} \|y - X\beta\|_2^2 + \lambda \|\beta\|_1 \right\}$$



Machine Learning (briefly)

Building a Prediction Model

- key insight: "regularization"
- slightly fancier than a multiple regression

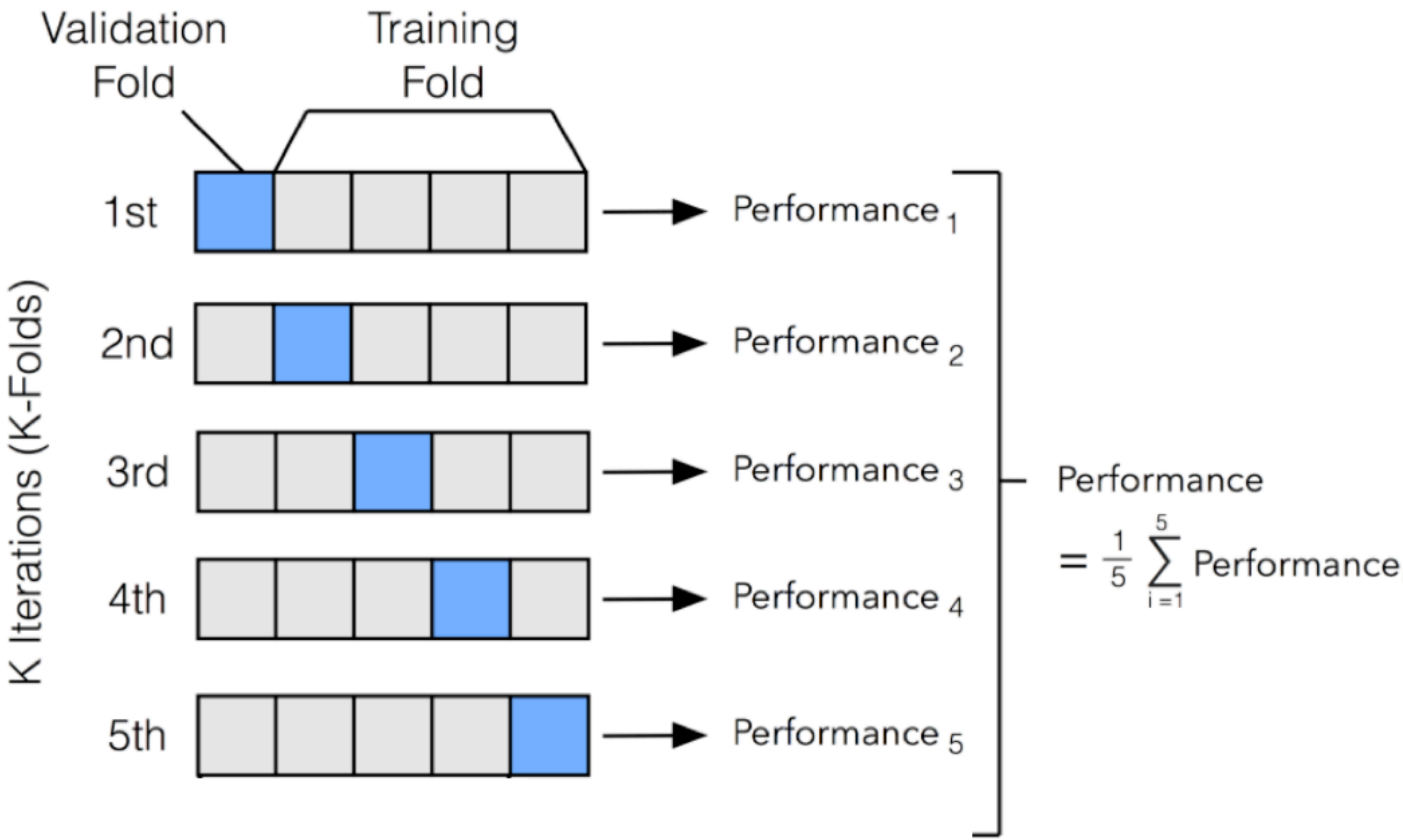
(see Tibshirani, 1996; Friedman, Hastie & Tibshirani, 2010)

Evaluating Model Accuracy

- key insight: "out of sample prediction"
- nested cross-validation

(see Stone, 1974; Varma & Simon, 2006)

Machine Learning (briefly)



Machine Learning (briefly)

Building a Prediction Model

- key insight: "regularization"
- slightly fancier than a multiple regression

(see Tibshirani, 1996; Friedman, Hastie & Tibshirani, 2010)

Evaluating Model Accuracy

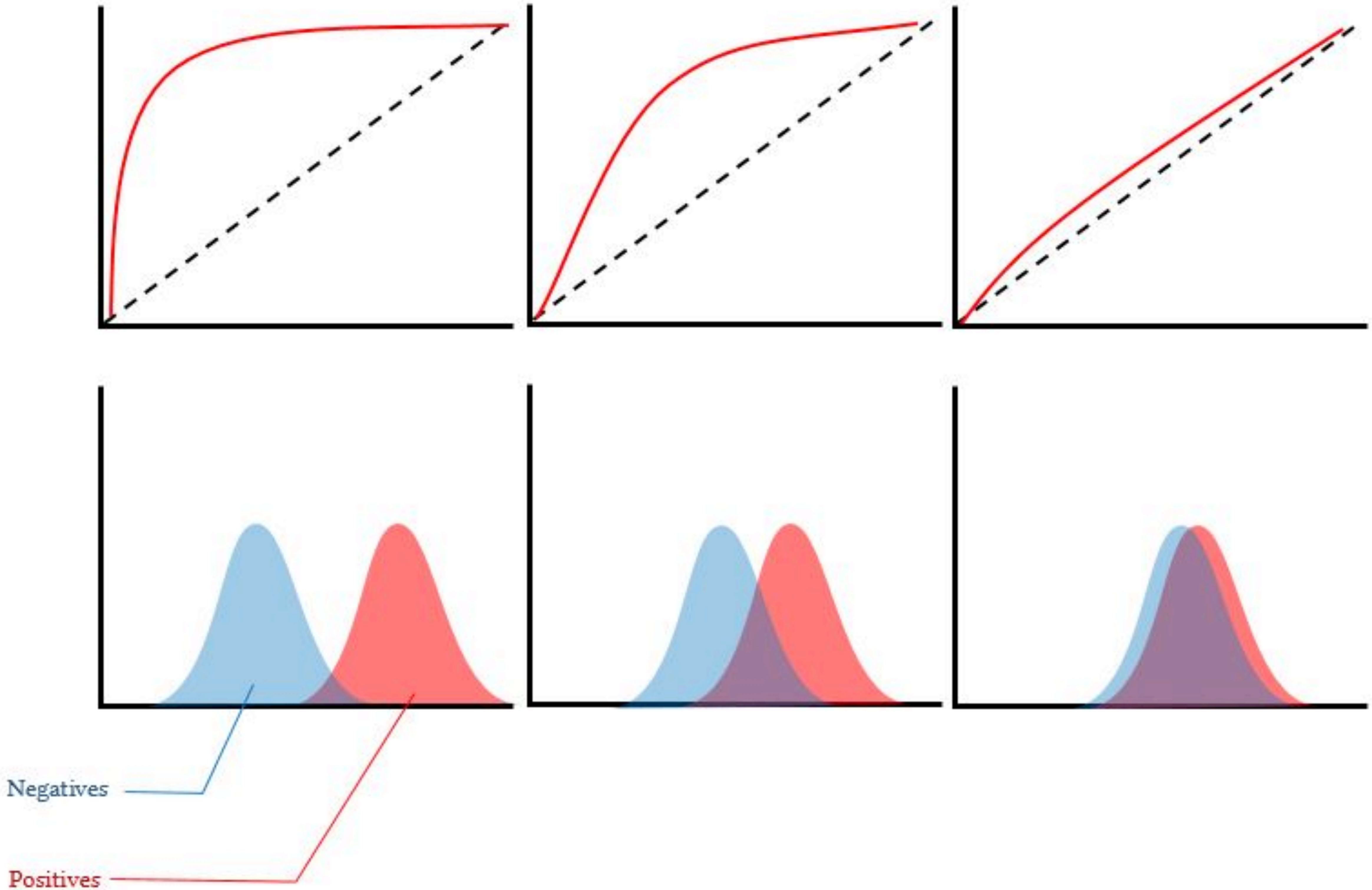
- key insight: "out of sample prediction"
- nested cross-validation

(see Stone, 1974; Varma & Simon, 2006)

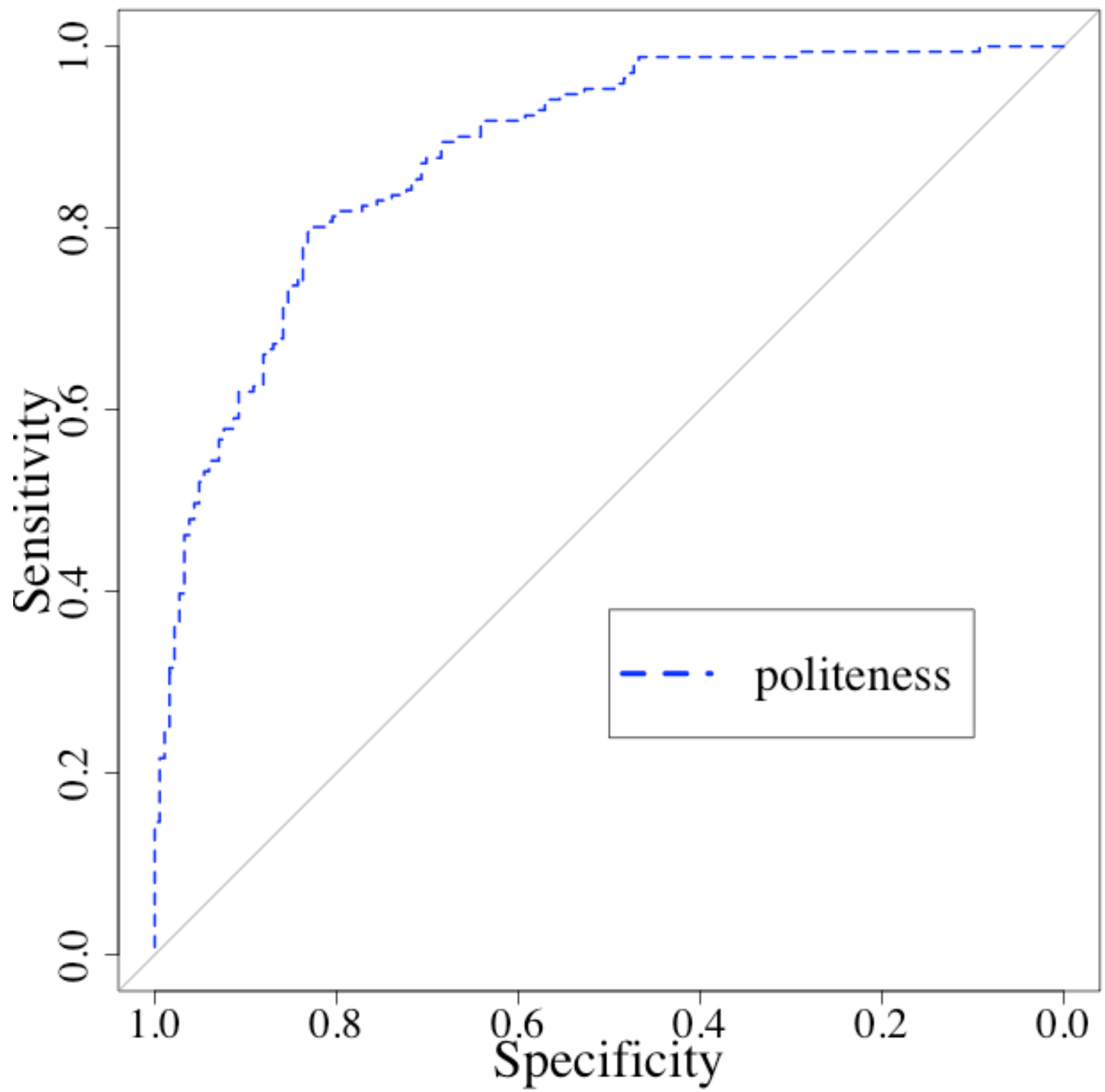
Measuring Model Accuracy

- key insight: "pairwise comparisons"
- Area Under Curve from ROC

Machine Learning (briefly)

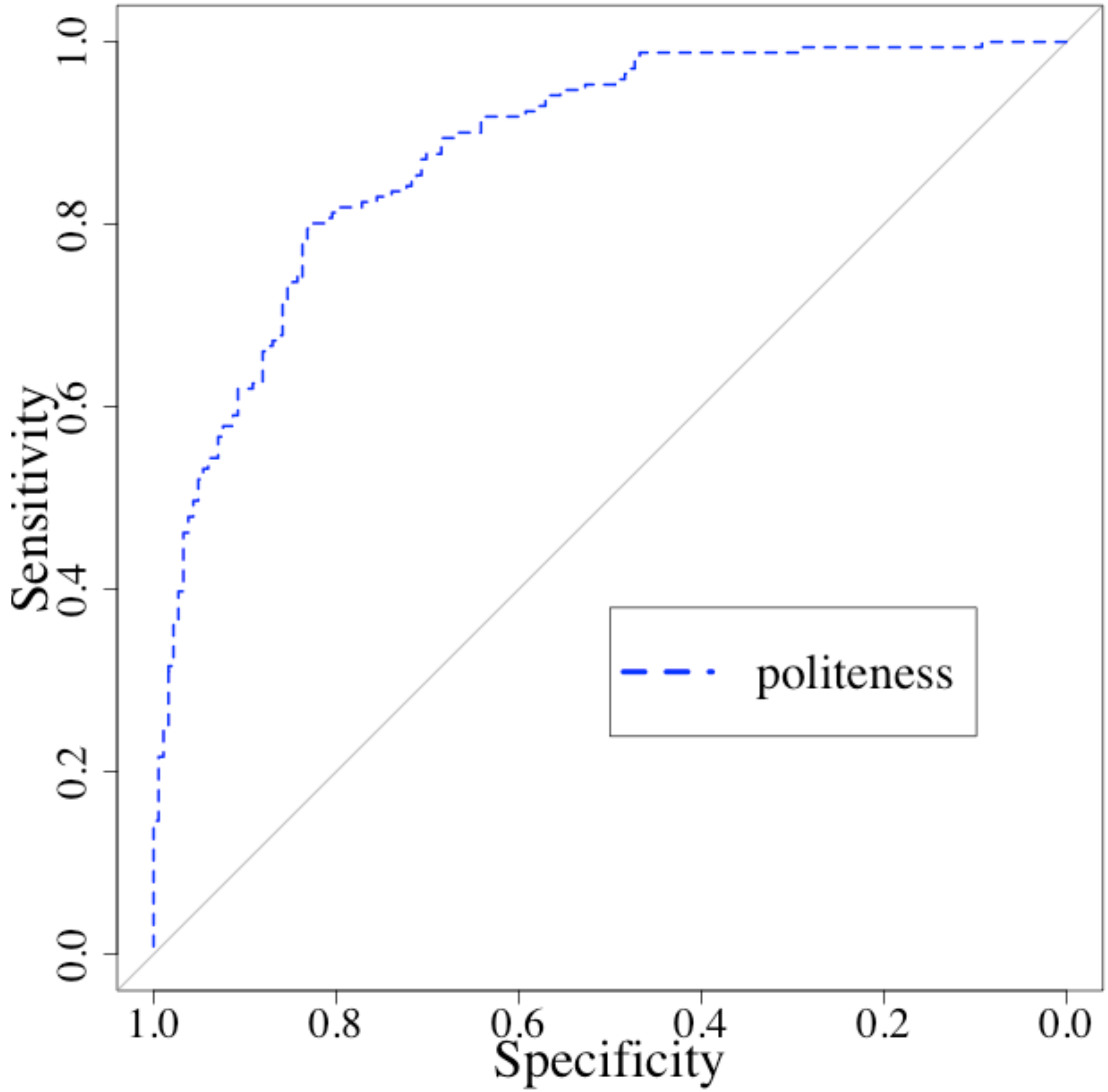


Communicating Warmth in …



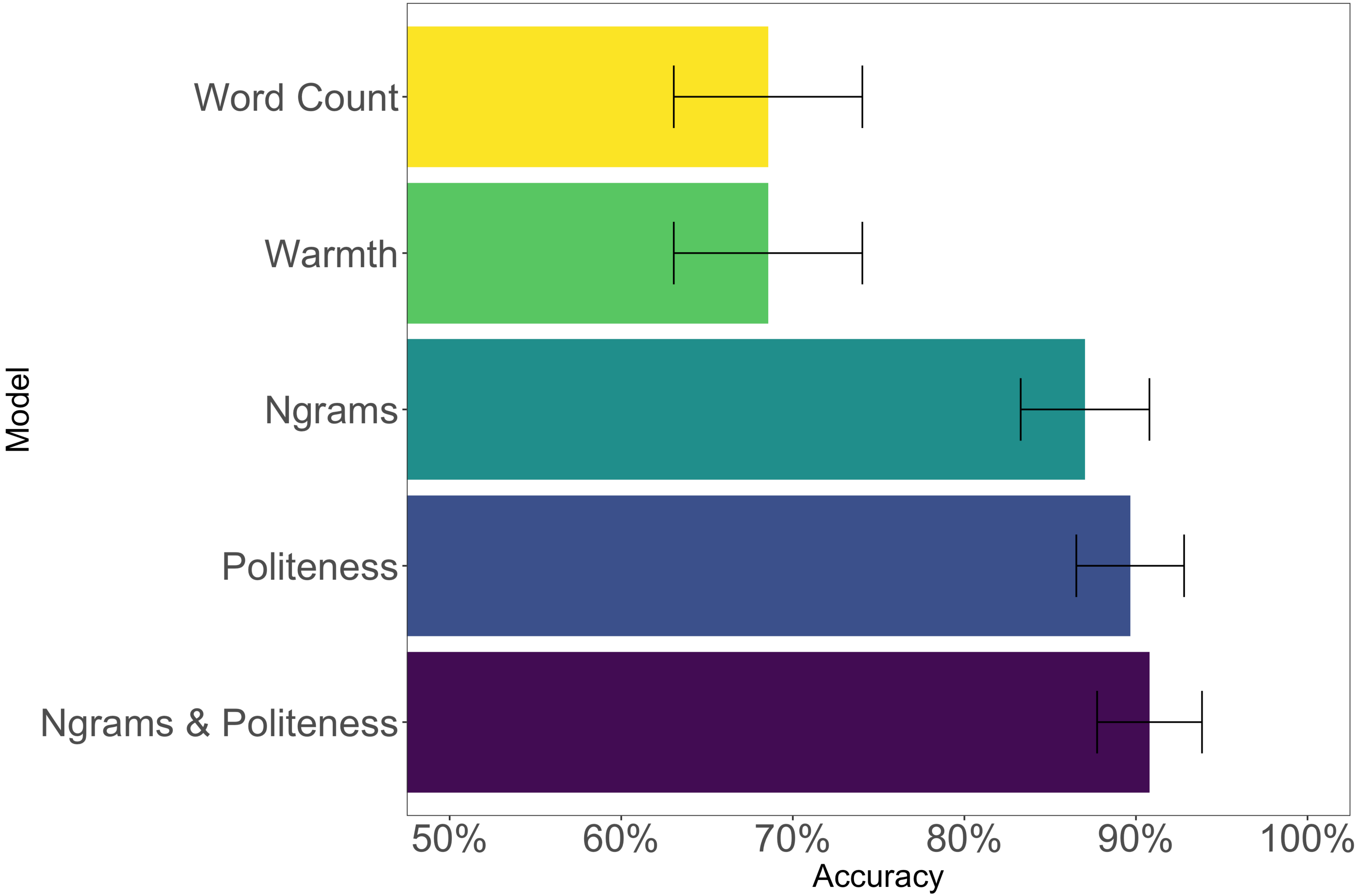
Communicating Warmth in …

Area Under the Curve: .883
95% CI: [.849,.917]



Communicating Warmth in …

Communicating Warmth in ...



Communicating Warmth in …

mTurkers can write phone offers! (n = 355)

- encouragement design - tough vs. warm instructions
- "ground truth" is treatment effect

Message	Condition
Hi, since this is a...	0
Hi, I saw your ad...	1
Hey, I hope you are...	1
Hi, I am interested...	0
Hi, I am interested...	0
I saw your add on...	0

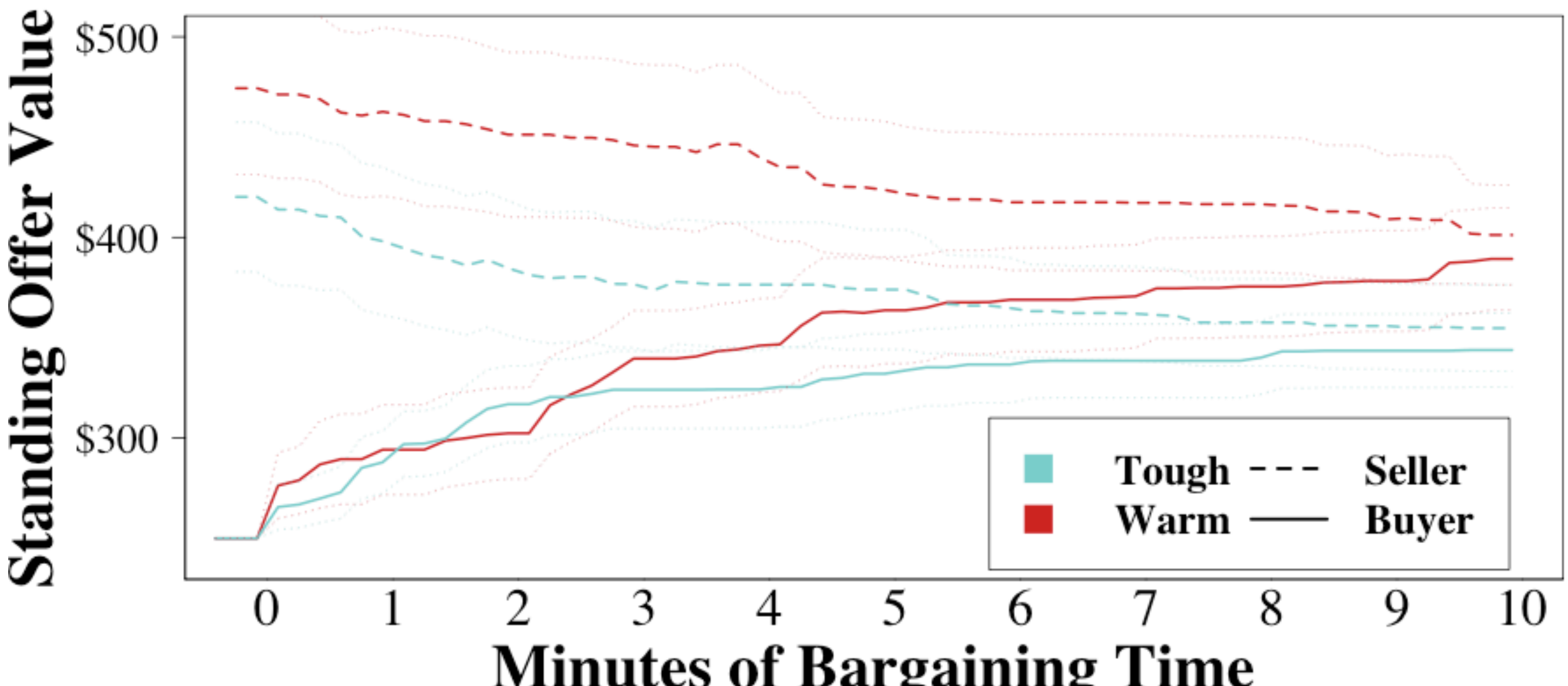
We want to build an algorithm that is:

- interpretable
- valid
- **scaleable**

Communicating Warmth in …

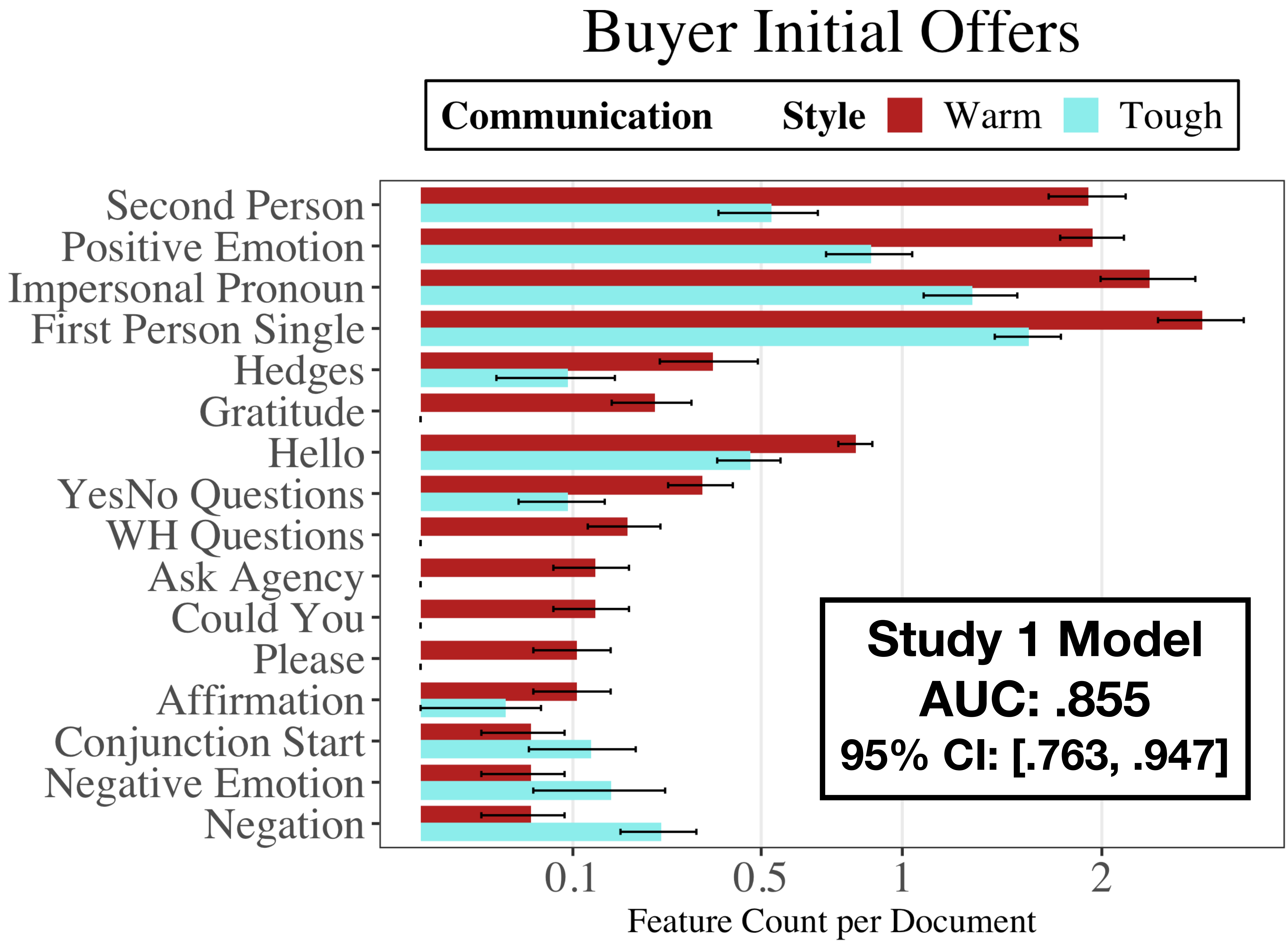
Warm offers earn worse final deals

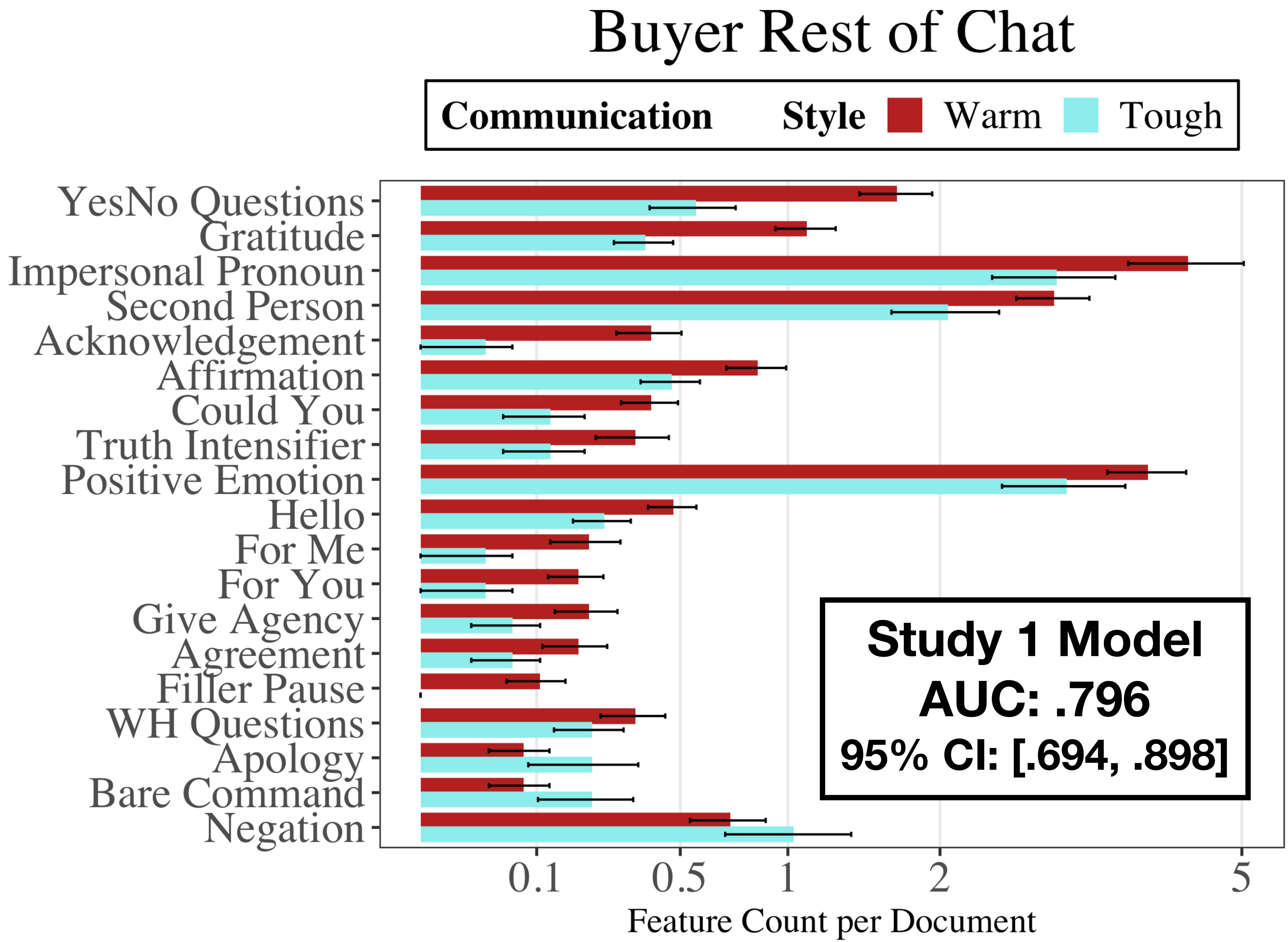
- incentivized lab experiment with dyads
- driven by early seller concessions



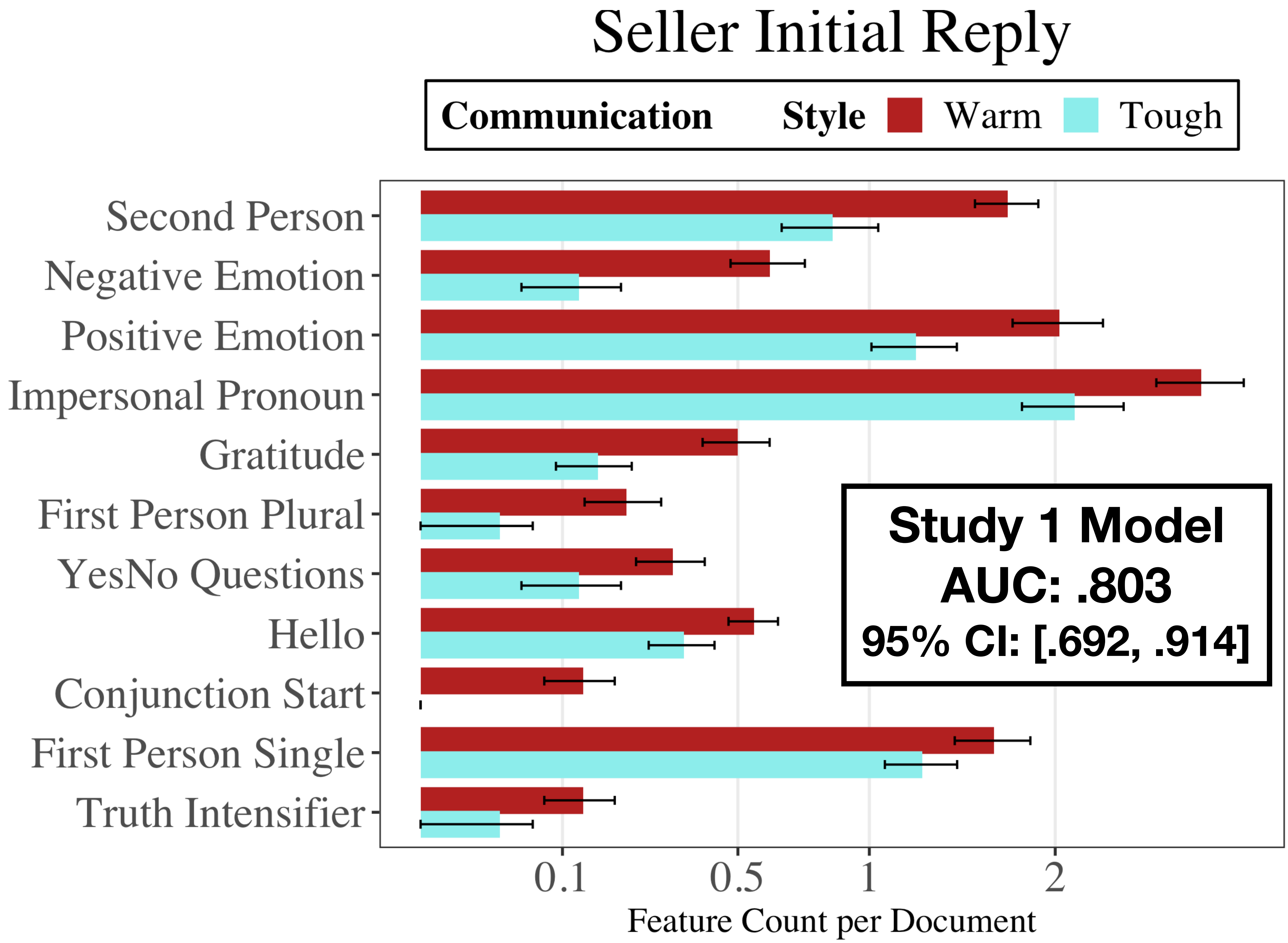
Communicating Warmth in …

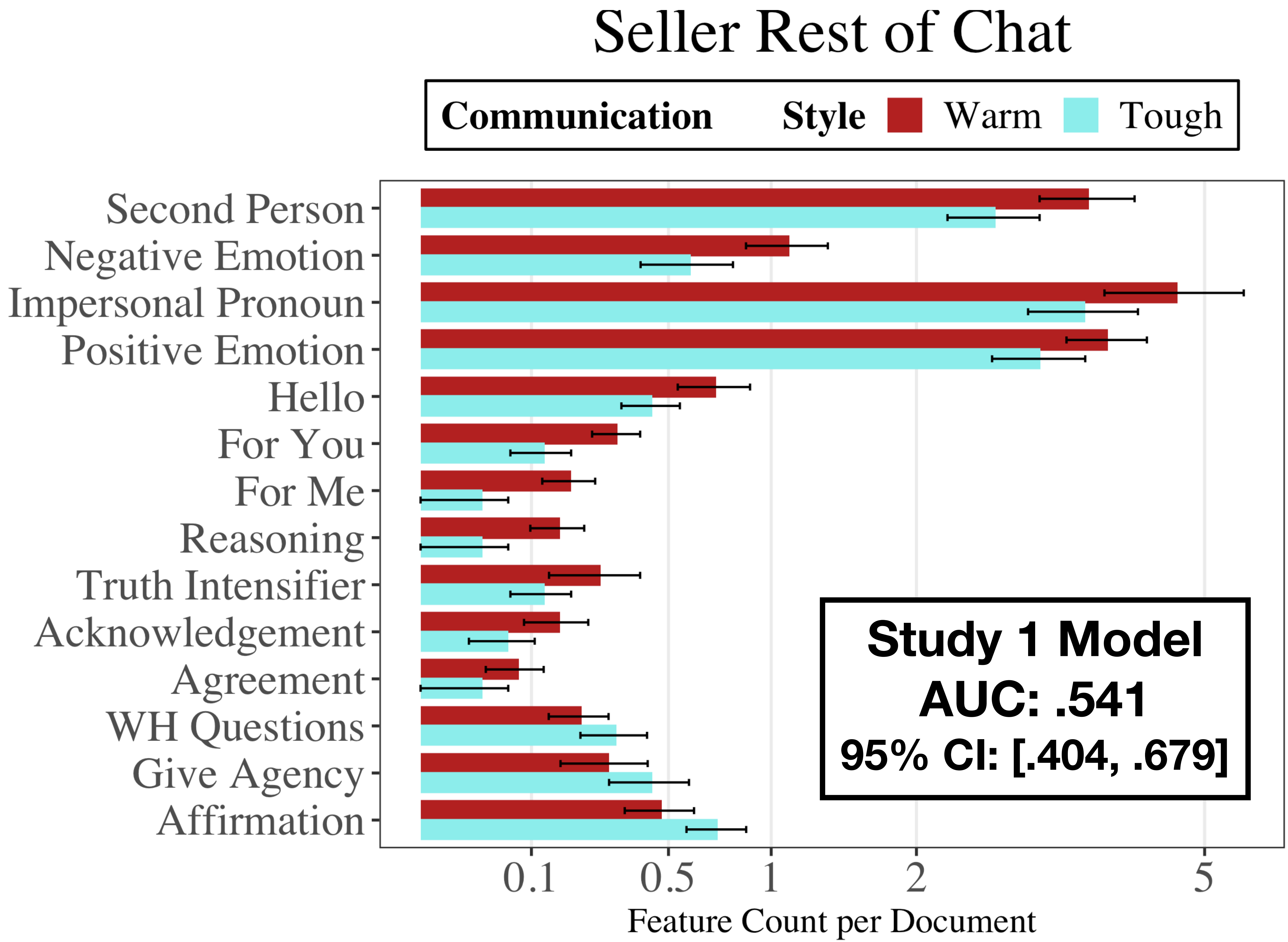
RStudio® Cloud


Buyer Initial Offers
Communication Style
Warm
Tough
Second Person
Positive Emotion
Impersonal Pronoun
First Person Single
Hedges
Gratitude
Hello
YesNo Questions
WH Questions
Ask Agency
Could You
Please
Affirmation
Conjunction Start
Negative Emotion
Negation
Study 1 Model
AUC: .855
95% CI: [.763, .947]
0.1
0.5
1
2
Feature Count per Document



Buyer Rest of Chat
Communication Style
Warm
Tough
YesNo Questions
Gratitude
Impersonal Pronoun
Second Person
Acknowledgement
Affirmation
Could You
Truth Intensifier
Positive Emotion
Hello
For Me
For You
Give Agency
Agreement
Filler Pause
WH Questions
Apology
Bare Command
Negation
Study 1 Model
AUC: .796
95% CI: [.694, .898]
0.1
0.5
1
2
5
Feature Count per Document


Seller Initial Reply
Communication Style
Warm
Tough
Second Person
Negative Emotion
Positive Emotion
Impersonal Pronoun
Gratitude
First Person Plural
YesNo Questions
Hello
Conjunction Start
First Person Single
Truth Intensifier
Study 1 Model
AUC: .803
95% CI: [.692, .914]
0.1
0.5
1
2
Feature Count per Document


Seller Rest of Chat
Communication Style
Warm
Tough
Second Person
Negative Emotion
Impersonal Pronoun
Positive Emotion
Hello
For You
For Me
Reasoning
Truth Intensifier
Acknowledgement
Agreement
WH Questions
Give Agency
Affirmation
0.1
0.5
1
2
5
Feature Count per Document
Study 1 Model
AUC: .541
95% CI: [.404, .679]

Politeness as Data

Politeness as Data

Politeness as treatment (IV)

Politeness as Data

Politeness as treatment (IV)

- listener response to politeness from another person

Politeness as Data

Politeness as treatment (IV)

- listener response to politeness from another person
- partners, confederates, incidental exposures

Politeness as Data

Politeness as treatment (IV)

- listener response to politeness from another person
- partners, confederates, incidental exposures

Politeness as outcome (DV)

- pure treatment effect (from emotion, framing…)

Politeness as Data

Politeness as treatment (IV)

- listener response to politeness from another person
- partners, confederates, incidental exposures

Politeness as outcome (DV)

- pure treatment effect (from emotion, framing…)
- politeness in reply to initial speaker

Politeness as Data

Politeness as treatment (IV)

- listener response to politeness from another person
- partners, confederates, incidental exposures

Politeness as outcome (DV)

- pure treatment effect (from emotion, framing…)
- politeness in reply to initial speaker

Politeness as mediator (IV & DV)

- effect of politeness induced in speaker on listener

What are the leaves?

Negotiations

Communicating Warmth in Distributive Negotiations is Surprisingly Counter-Productive

(Jeong et al., 2018)

Organizational Conflict

Conversational Receptiveness: Improving Engagement with Opposing Views

(Yeomans et al., 2020)

Managing Disagreement

Managing Disagreement

What you are thinking

(Turner & Crisp, 2010; Bruneau & Saxe, 2012; Kteily et al., 2018; Schroeder & Epley, 2018; Minson, Chen & Tinsley, 2019)

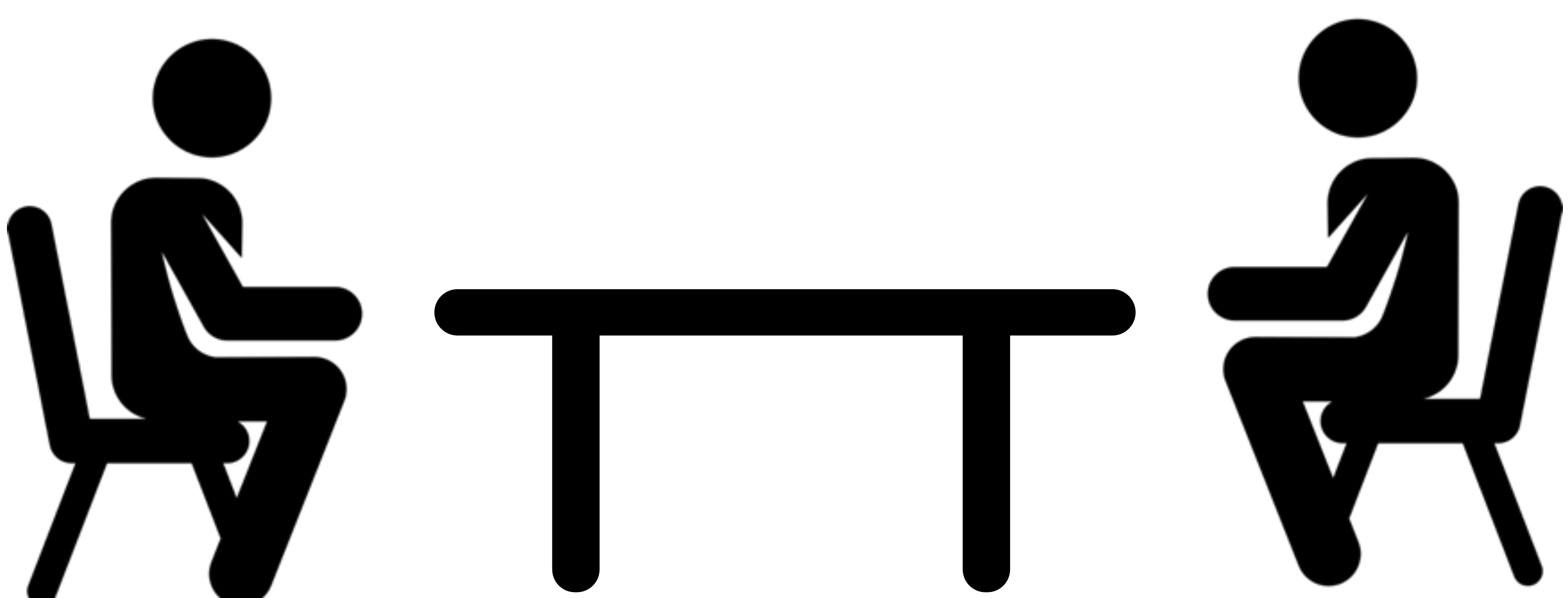
Managing Disagreement

What you are thinking

(Turner & Crisp, 2010; Bruneau & Saxe, 2012; Kteily et al., 2018;
Schroeder & Epley, 2018; Minson, Chen & Tinsley, 2019)

Who you are talking to

(Mannix & Neale, 2005; Pettigrew & Tropp, 2006;
MacInnis & Page-Gould, 2015; Paluck, Green & Green, 2017;
Yeomans et al., 2018; Bail et al., 2018)



Managing Disagreement

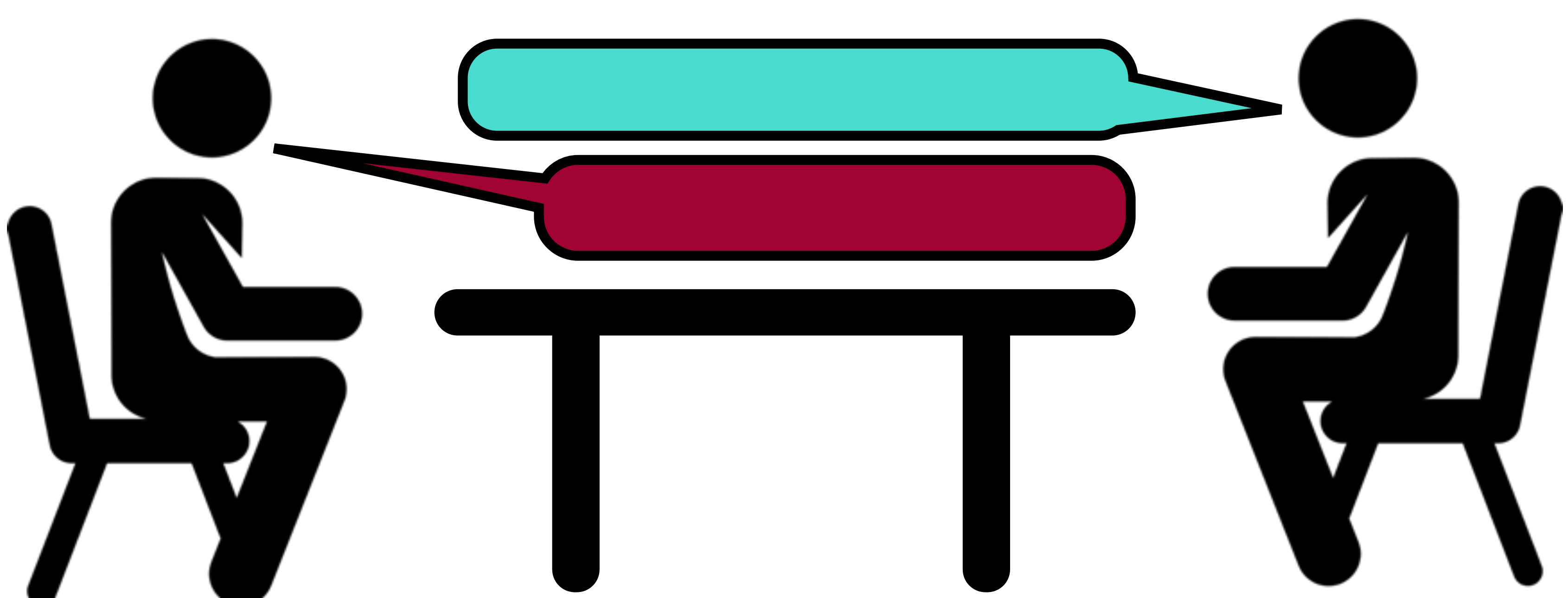
What you are thinking

(Turner & Crisp, 2010; Bruneau & Saxe, 2012; Kteily et al., 2018; Schroeder & Epley, 2018; Minson, Chen & Tinsley, 2019)

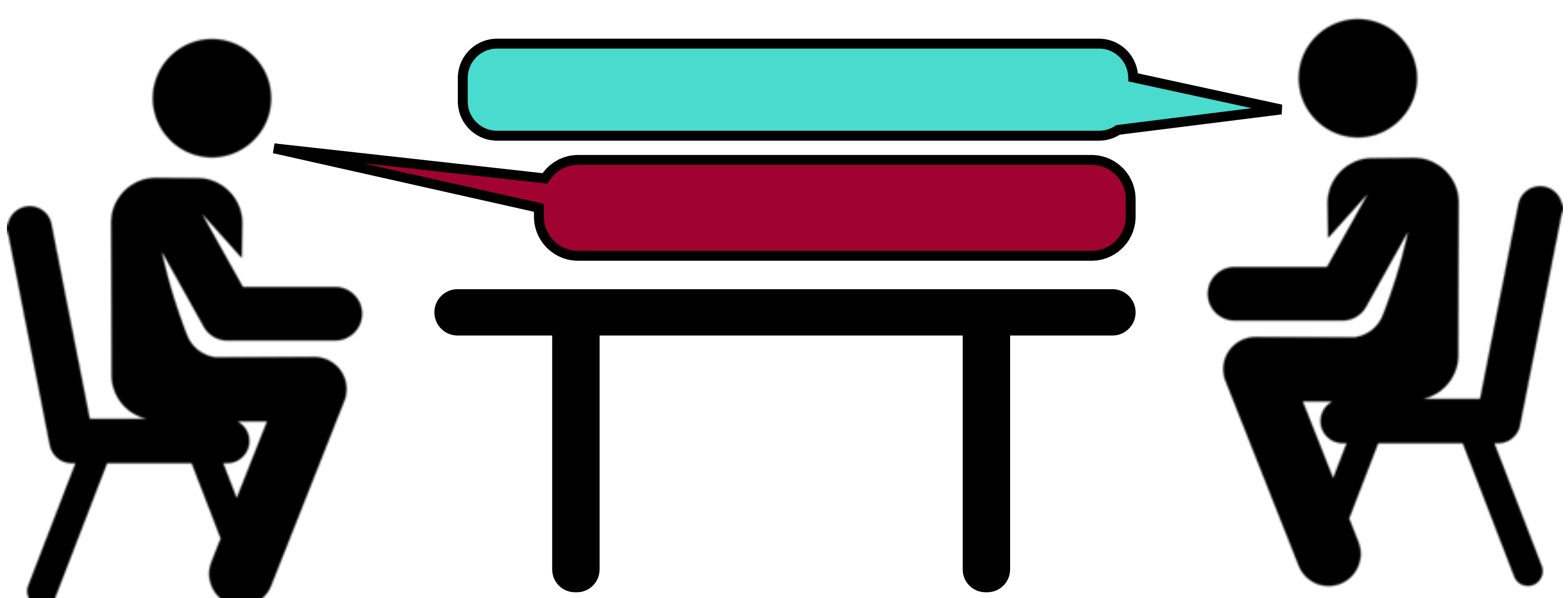
Who you are talking to

(Mannix & Neale, 2005; Pettigrew & Tropp, 2006; MacInnis & Page-Gould, 2015; Paluck, Green & Green, 2017; Yeomans et al., 2018; Bail et al., 2018)

What you are saying

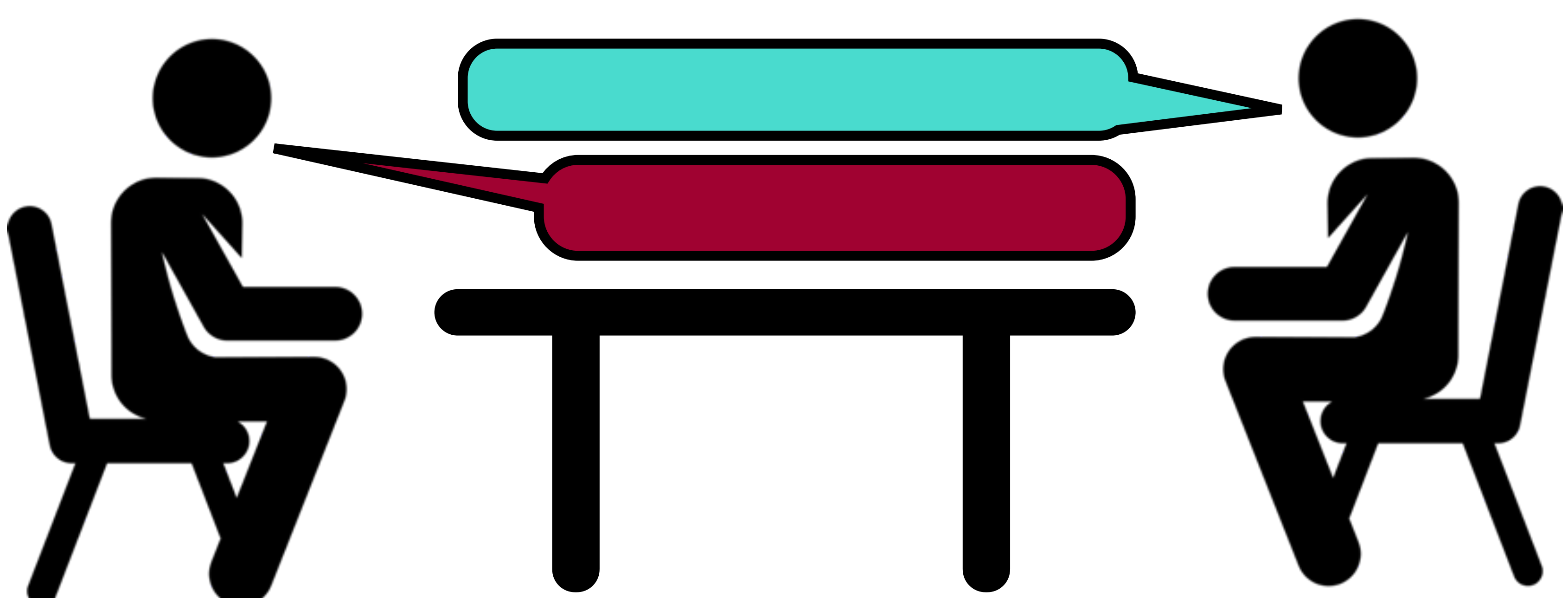


Conversational Receptiveness



Conversational Receptiveness

The behavior in conversation that communicates thoughtful consideration of opposing views

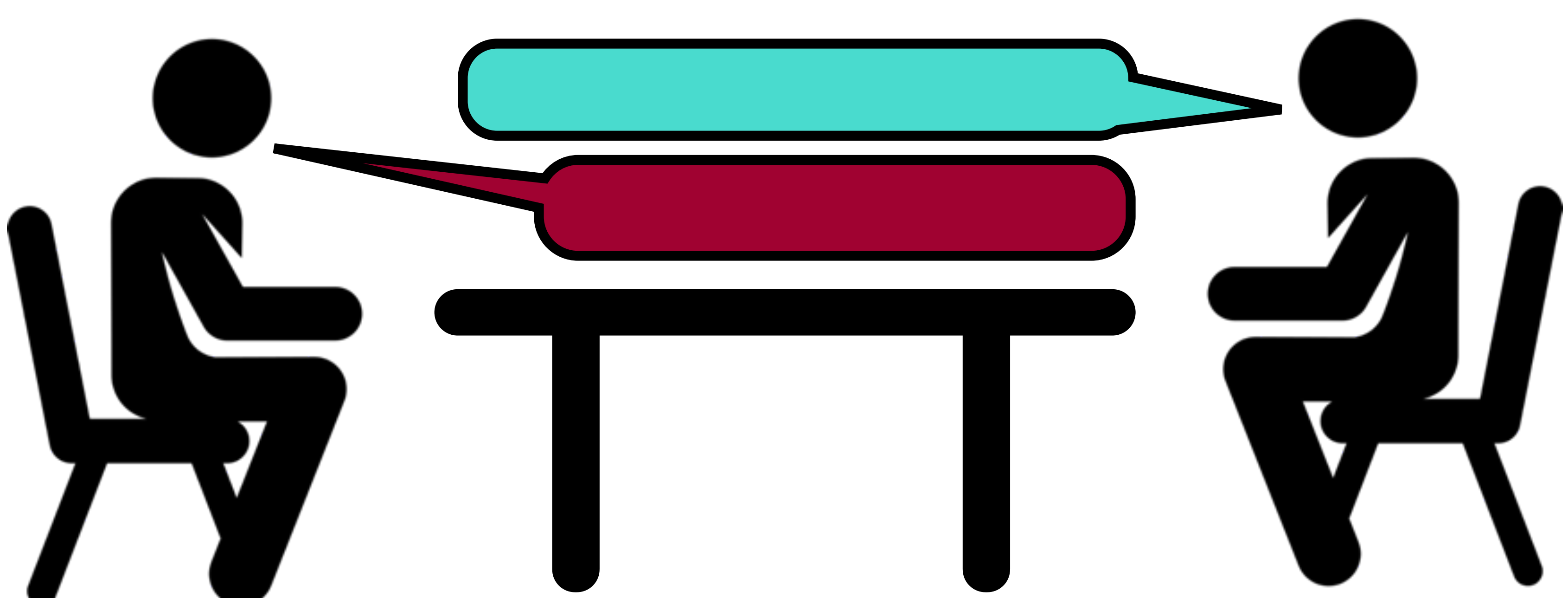


Conversational Receptiveness

...is measurable from behavioral data

...improves the health of conversations

...is misunderstood by people in conflict



Conversational Receptiveness

...is measurable from behavioral data

...improves the health of conversations

...is misunderstood by people in conflict

Conversational Receptiveness

...is measurable from behavioral data

Study 1 - Mechanical Turk

...improves the health of conversations

Study 2 - HarvardX Online Courses

Study 3 - Wikipedia Editors

...is misunderstood by people in conflict

Study 4 - Local Government Officials

Study 5 - The Receptiveness Recipe

Conversational Receptiveness

...is measurable from behavioral data

Study 1 - Mechanical Turk

...improves the health of conversations

Study 2 - HarvardX Online Courses

Study 3 - Wikipedia Editors

...is misunderstood by people in conflict

Study 4 - Local Government Officials

Study 5 - The Receptiveness Recipe

https://osf.io/2n59b/

OPEN MATERIALS

OPEN DATA

PREREGISTERED

Study 1: Measuring Disagreement

Study 1: Measuring Disagreement

1. Collect conversations between people who disagree.

Study 1: Measuring Disagreement

1. Collect conversations between people who disagree.

2. Ask other people to rate their receptiveness.

Study 1: Measuring Disagreement

1. Collect conversations between people who disagree.

2. Ask other people to rate their receptiveness.

3. Train an algorithm to rate receptiveness automatically.

Study 1: Measuring Disagreement

1. Collect conversations between people who disagree.

2. Ask other people to rate their receptiveness.

3. Train an algorithm to rate receptiveness automatically.

We want to build an algorithm that is:

Study 1: Measuring Disagreement

1. Collect conversations between people who disagree.

2. Ask other people to rate their receptiveness.

3. Train an algorithm to rate receptiveness automatically.

We want to build an algorithm that is:

- scaleable

Study 1: Measuring Disagreement

1. Collect conversations between people who disagree.

2. Ask other people to rate their receptiveness.

3. Train an algorithm to rate receptiveness automatically.

We want to build an algorithm that is:

- scaleable
- interpretable

Study 1: Measuring Disagreement

1. Collect conversations between people who disagree.

2. Ask other people to rate their receptiveness.

3. Train an algorithm to rate receptiveness automatically.

We want to build an algorithm that is:

- scaleable
- interpretable
- valid

How Humans Rate Receptiveness

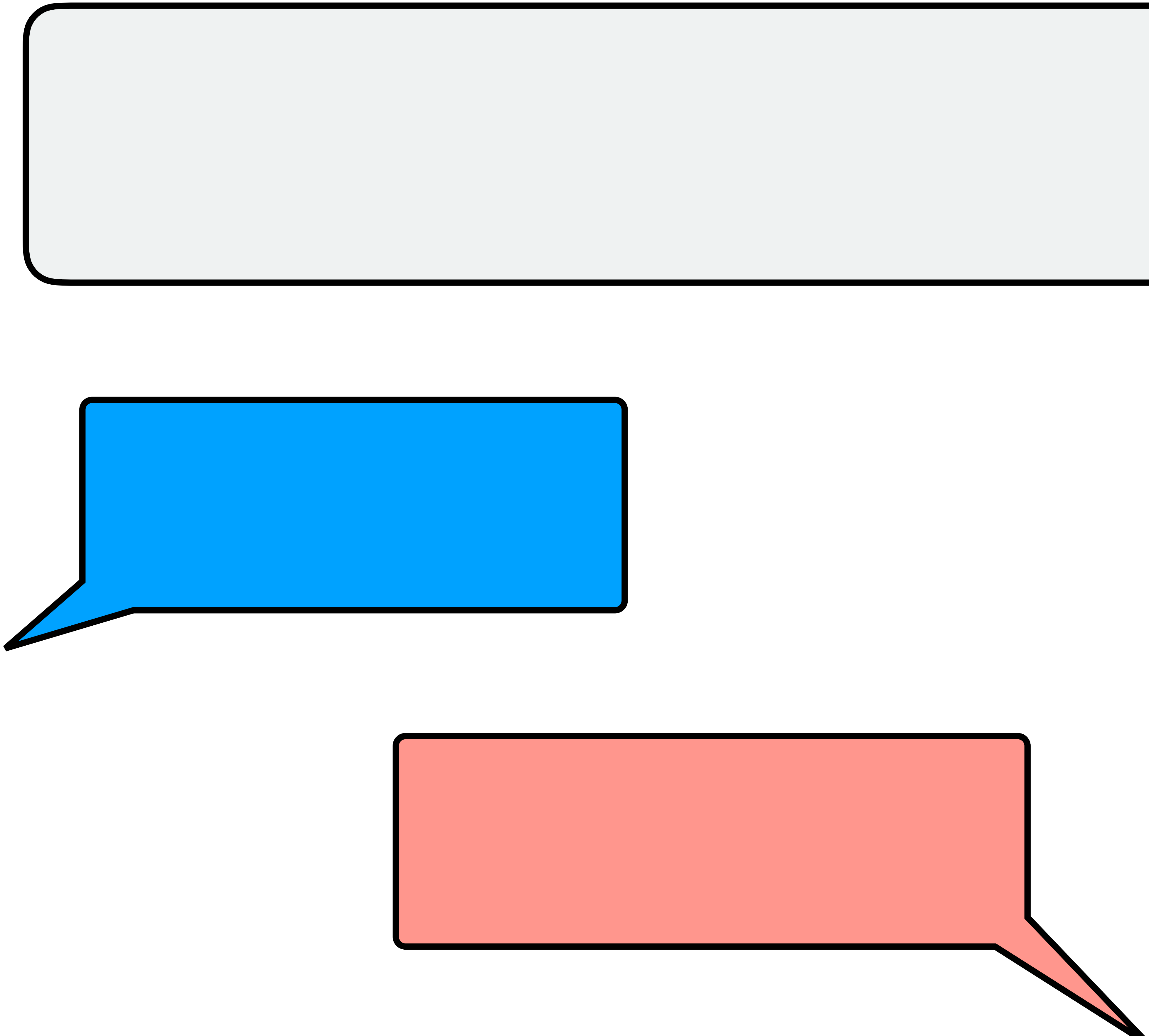
- On this issue, the respondent seems like a person who finds listening to opposing views on this issue informative.
- The respondent seems to feel that this issue is just not up for debate.
- It seems that listening to people with views that oppose their own tends to make the respondent angry.
- The respondent seems like a person who values interactions with people who hold strong views opposite to their own on this issue.

4 of 18 items, based on "Dispositional Receptiveness"

(Minson, Tinsley & Chen, 2018)

Study 1A Conversations

Study 1A Conversations

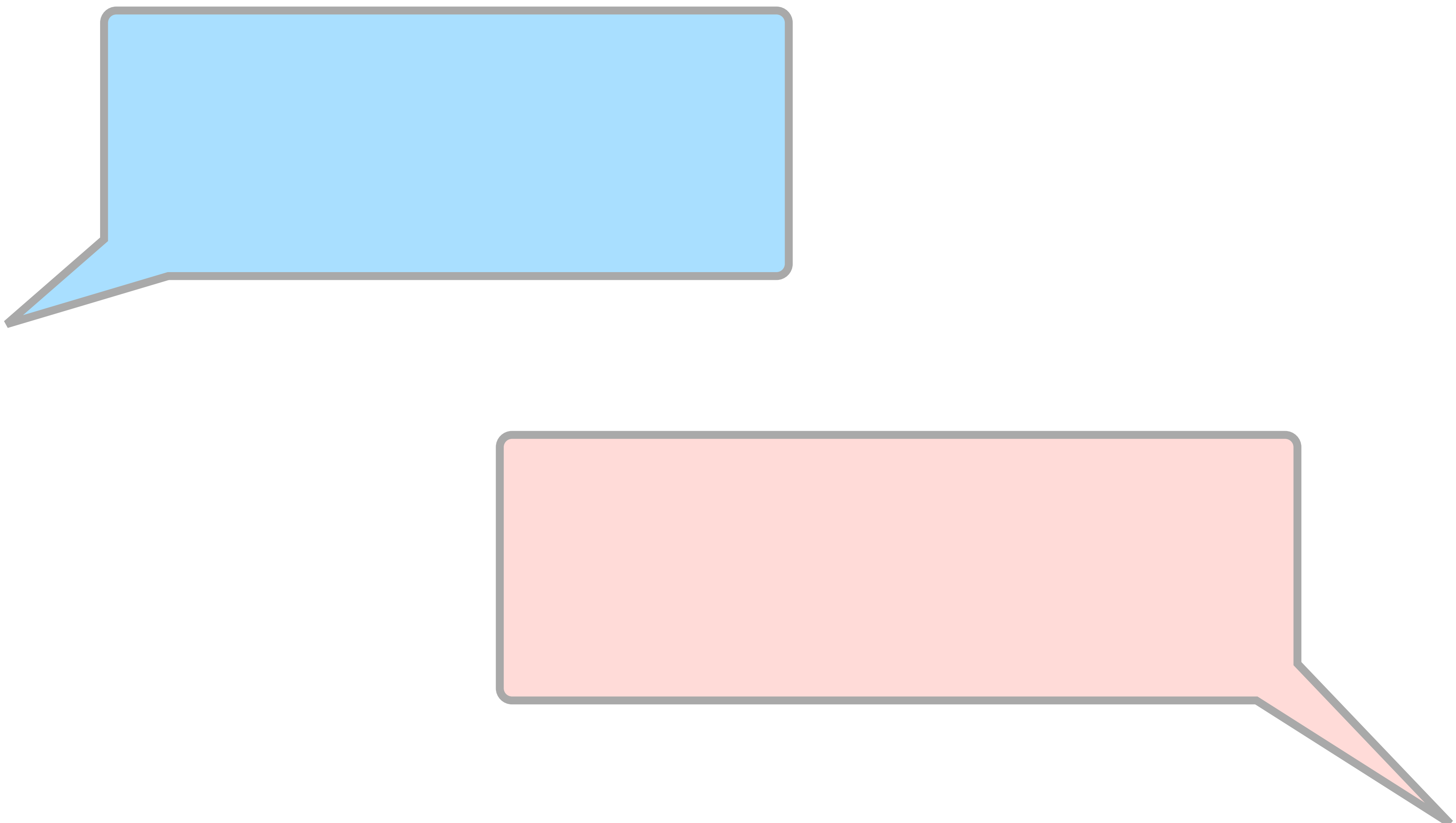


Study 1A Conversations

The public reaction to recent confrontations between police and minority crime suspects has been overblown.

Issue Prompt

1 of 2



Study 1A Conversations

The public reaction to recent confrontations between police and minority crime suspects has been overblown.

Issue Prompt

1 of 2

No, it hasn't!

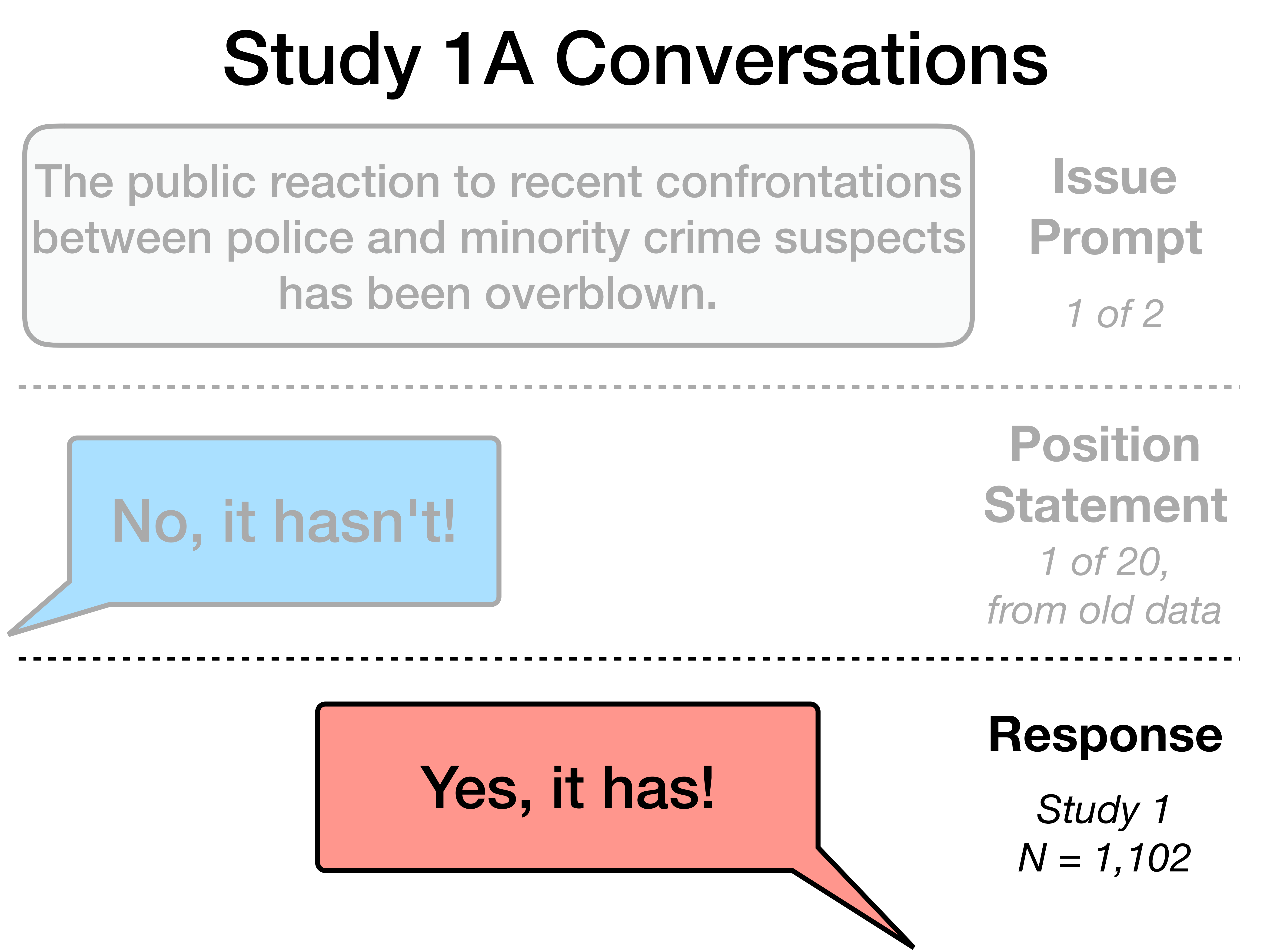
Position Statement

1 of 20, from old data

Example Position Statement

The public reaction has not been overblown, if anything it is severely muted. Recent confrontations are simply making visible issues that have existed for a very long time. Lynchings and killings of minorities have happened throughout American history. However, now we have proof in real time through cell phone videos and Facebook Live. There are real issues between police and the communities they serve that are only being addressed because of the attention being paid through Black Lives Matter and other protests. This is how things improve, even if it is hard and difficult to discuss.

M = 105 words, SD = 34


Study 1A Conversations
The public reaction to recent confrontations between police and minority crime suspects has been overblown.
Issue Prompt
1 of 2
No, it hasn't!
Position Statement
1 of 20, from old data
Yes, it has!
Response
Study 1
N = 1,102

Example Responses

M = 66 words, SD = 30

I understand what you are saying. There probably is some truth to the fact that these issues have been hidden for a long time. However, coming from St. Louis and witnessing the Ferguson riots, I can also see how things can be blown out of proportion and make people feel that it is worse than it is. I agree real problems exist, but possibly sometimes attention is drawn in the wrong places.

Over-reacting to police confrontations, can be deadly to the public in general. When animosity towards the police rises, as it has in Chicago, police do not feel safe, going into the ghetto neighborhoods. Therefore those people, in those neighborhood, literally, have to fend for themselves, because if they need the police and call for their help, the police can't help those in need there, because they will likely be shot at themselves.

Which person is more receptive?

I understand what you are saying. There probably is some truth to the fact that these issues have been hidden for a long time. However, coming from St. Louis and witnessing the Ferguson riots, I can also see how things can be blown out of proportion and make people feel that it is worse than it is. I agree real problems exist, but possibly sometimes attention is drawn in the wrong places.

Over-reacting to police confrontations, can be deadly to the public in general. When animosity towards the police rises, as it has in Chicago, police do not feel safe, going into the ghetto neighborhoods. Therefore those people, in those neighborhood, literally, have to fend for themselves, because if they need the police and call for their help, the police can't help those in need there, because they will likely be shot at themselves.

Which person is more receptive?

Receptive Response *(96th percentile)*

I understand what you are saying. There probably is some truth to the fact that these issues have been hidden for a long time. However, coming from St. Louis and witnessing the Ferguson riots, I can also see how things can be blown out of proportion and make people feel that it is worse than it is. I agree real problems exist, but possibly sometimes attention is drawn in the wrong places.

Unreceptive Response *(2nd percentile)*

Over-reacting to police confrontations, can be deadly to the public in general. When animosity towards the police rises, as it has in Chicago, police do not feel safe, going into the ghetto neighborhoods. Therefore those people, in those neighborhood, literally, have to fend for themselves, because if they need the police and call for their help, the police can't help those in need there, because they will likely be shot at themselves.

Conversational Receptiveness

mTurkers can write text (n=1,102)

Conversational Receptiveness

mTurkers can write text (n=1,102)
mTurkers can also rate text (n=1,302)

Conversational Receptiveness

mTurkers can write text (n=1,102)

mTurkers can also rate text (n=1,302)

- “ground truth” is average ratings from opponents

Conversational Receptiveness

mTurkers can write text (n=1,102)

mTurkers can also rate text (n=1,302)

- "ground truth" is average ratings from opponents

Message	Rating
well that's an interesting opinion you have...	2.56
I agree with you but I have never understood...	5.04
I understand your viewpoint here, but I...	4.63
If even one "accidental" death happens...	3.13
You also have to look at the police officer's...	4.03
I like that you treat both sides of the...	6.34

Conversational Receptiveness

mTurkers can write text (n=1,102)

mTurkers can also rate text (n=1,302)

- "ground truth" is average ratings from opponents

Message	Rating
well that's an interesting opinion you have...	2.56
I agree with you but I have never understood...	5.04
I understand your viewpoint here, but I...	4.63
If even one "accidental" death happens...	3.13
You also have to look at the police officer's...	4.03
I like that you treat both sides of the...	6.34

We want to build an algorithm that is:

- interpretable
- valid
- scaleable

Back to the Cloud...

Two Challenges to Generalizability

Topic Specificity

- receptivity may vary by topic

Two Challenges to Generalizability

Topic Specificity

- receptivity may vary by topic
- key concept: "transfer learning"

Two Challenges to Generalizability

Topic Specificity

- receptivity may vary by topic
- key concept: "transfer learning"

Training Data → **Test Data**

BLM → Sexual Assault

Two Challenges to Generalizability

Topic Specificity

- receptivity may vary by topic
- key concept: "transfer learning"

Training Data		Test Data
BLM	→	Sexual Assault
Sexual Assault	→	BLM

Back to the Cloud...

Two Challenges to Generalizability

Context Specificity

- some people more receptive

Two Challenges to Generalizability

Context Specificity

- some people more receptive

- 20 prompts! Too many for splits

Two Challenges to Generalizability

Context Specificity

- some people more receptive

- 20 prompts! Too many for splits

- key concept: matched pairs accuracy

Two Challenges to Generalizability

Context Specificity

- some people more receptive

- 20 prompts! Too many for splits

- key concept: matched pairs accuracy

Turn 1 → Turn 2

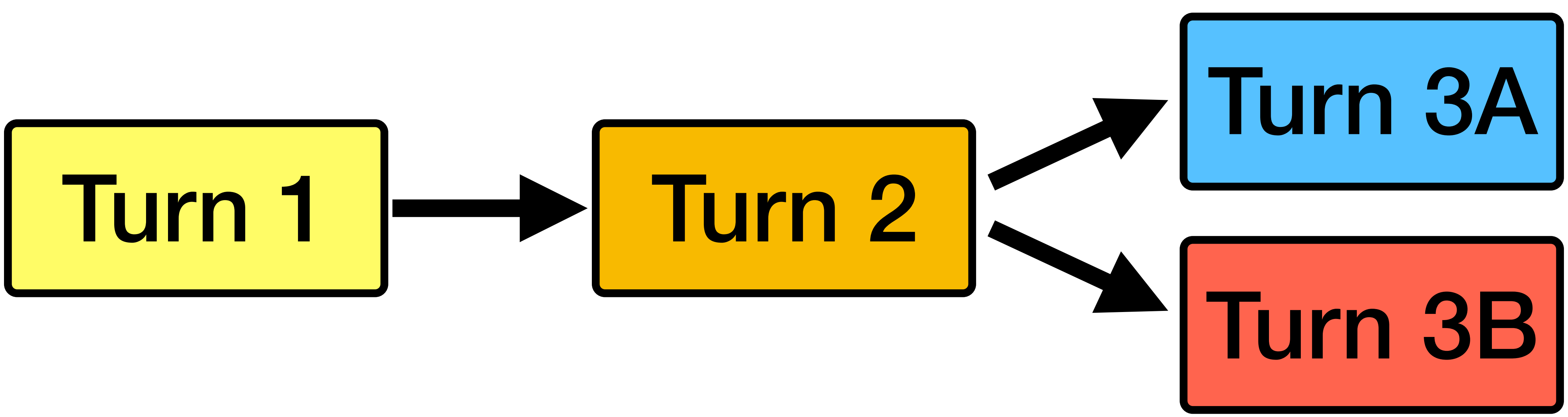
Two Challenges to Generalizability

Context Specificity

- some people more receptive

- 20 prompts! Too many for splits

- key concept: matched pairs accuracy



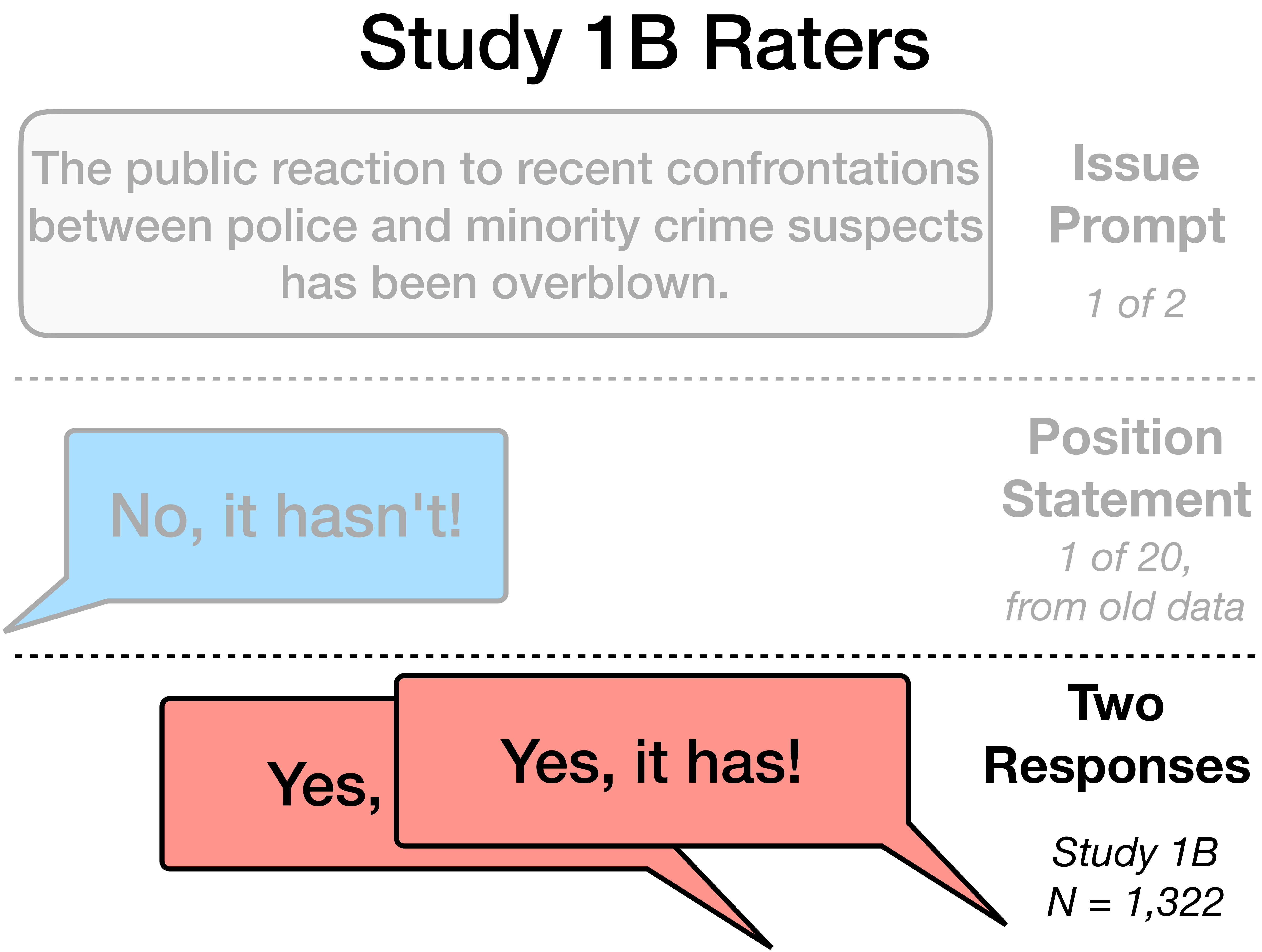
Which person is more receptive?

Receptive Response *(96th percentile)*

I understand what you are saying. There probably is some truth to the fact that these issues have been hidden for a long time. However, coming from St. Louis and witnessing the Ferguson riots, I can also see how things can be blown out of proportion and make people feel that it is worse than it is. I agree real problems exist, but possibly sometimes attention is drawn in the wrong places.

Unreceptive Response *(2nd percentile)*

Over-reacting to police confrontations, can be deadly to the public in general. When animosity towards the police rises, as it has in Chicago, police do not feel safe, going into the ghetto neighborhoods. Therefore those people, in those neighborhood, literally, have to fend for themselves, because if they need the police and call for their help, the police can't help those in need there, because they will likely be shot at themselves.


Study 1B Raters
The public reaction to recent confrontations between police and minority crime suspects has been overblown.
Issue Prompt
1 of 2
No, it hasn't!
Position Statement
1 of 20, from old data
Yes,
Yes, it has!
Two Responses
Study 1B
N = 1,322

Back to the Cloud...

Which person is more receptive?

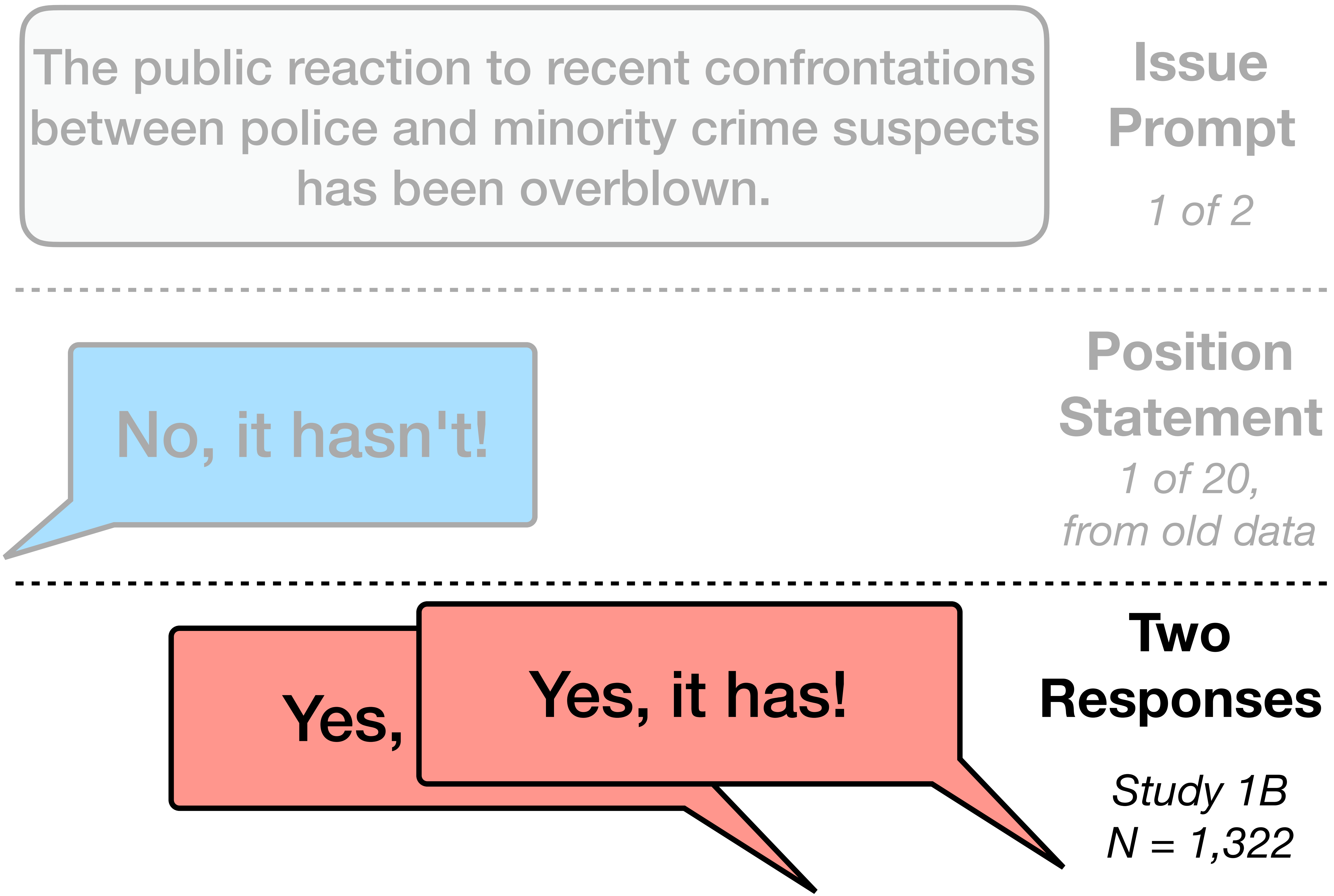
Receptive Response *(96th percentile)*

I understand what you are saying. There probably is some truth to the fact that these issues have been hidden for a long time. However, coming from St. Louis and witnessing the Ferguson riots, I can also see how things can be blown out of proportion and make people feel that it is worse than it is. I agree real problems exist, but possibly sometimes attention is drawn in the wrong places.

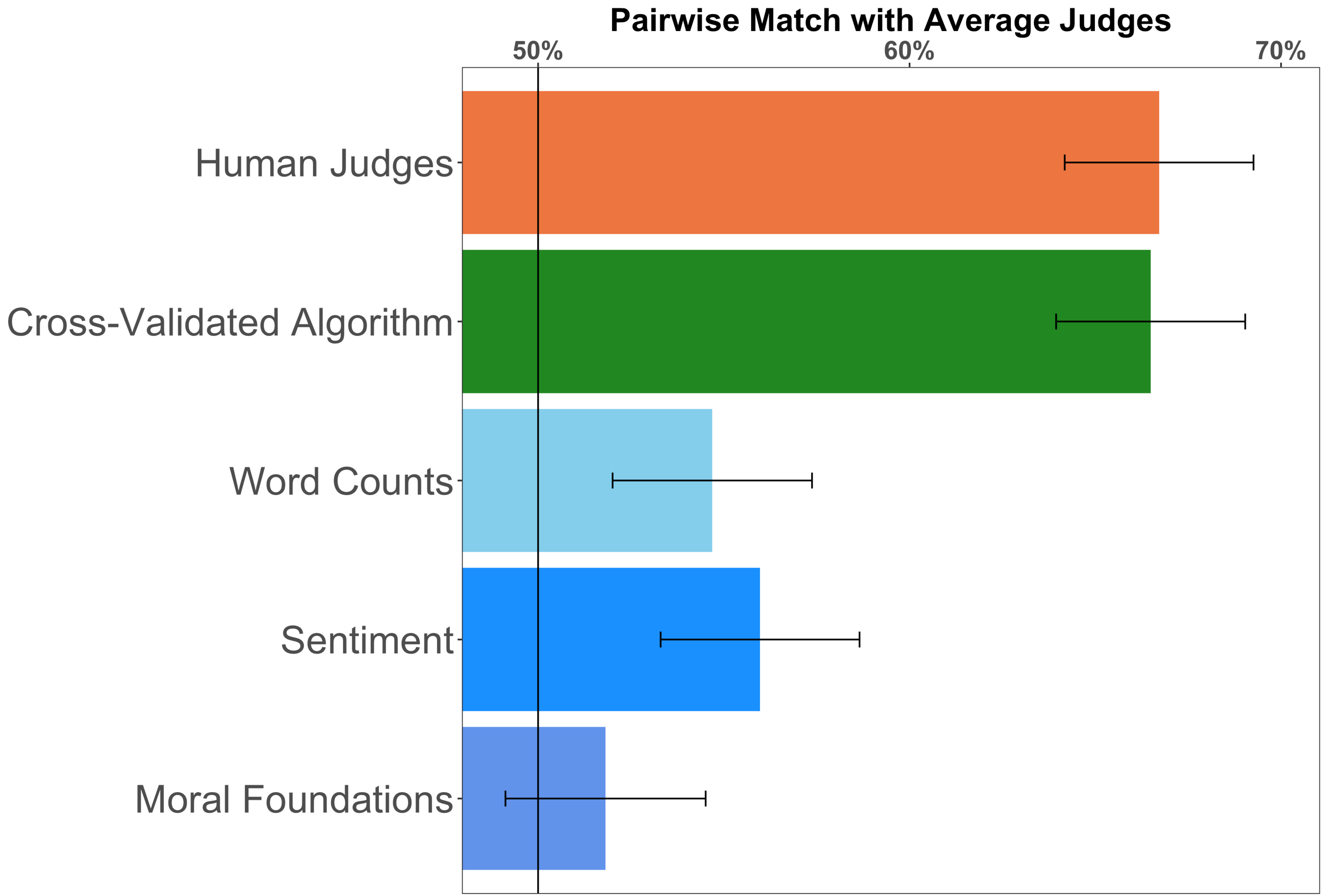
Unreceptive Response *(2nd percentile)*

Over-reacting to police confrontations, can be deadly to the public in general. When animosity towards the police rises, as it has in Chicago, police do not feel safe, going into the ghetto neighborhoods. Therefore those people, in those neighborhood, literally, have to fend for themselves, because if they need the police and call for their help, the police can't help those in need there, because they will likely be shot at themselves.

Study 1B Raters

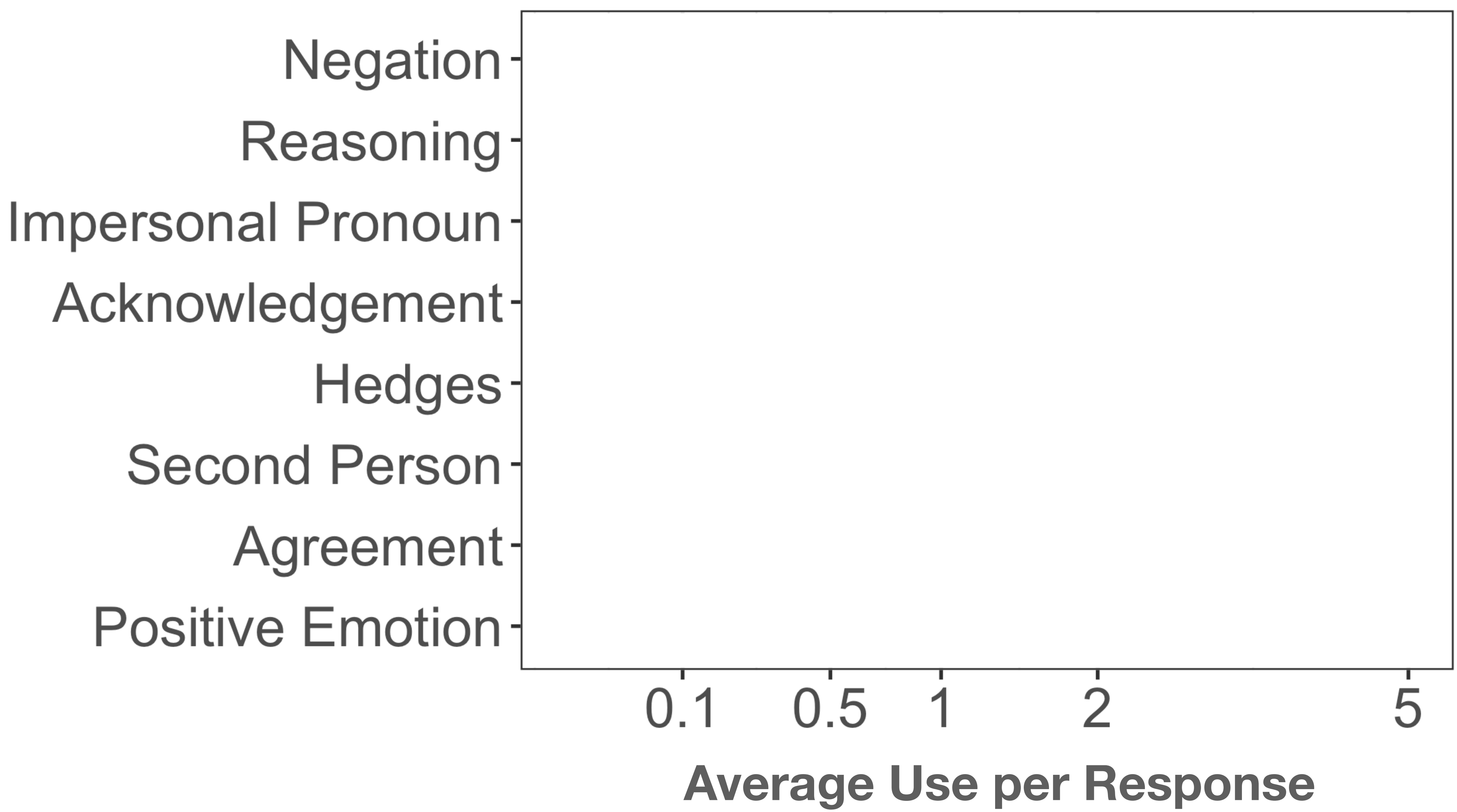


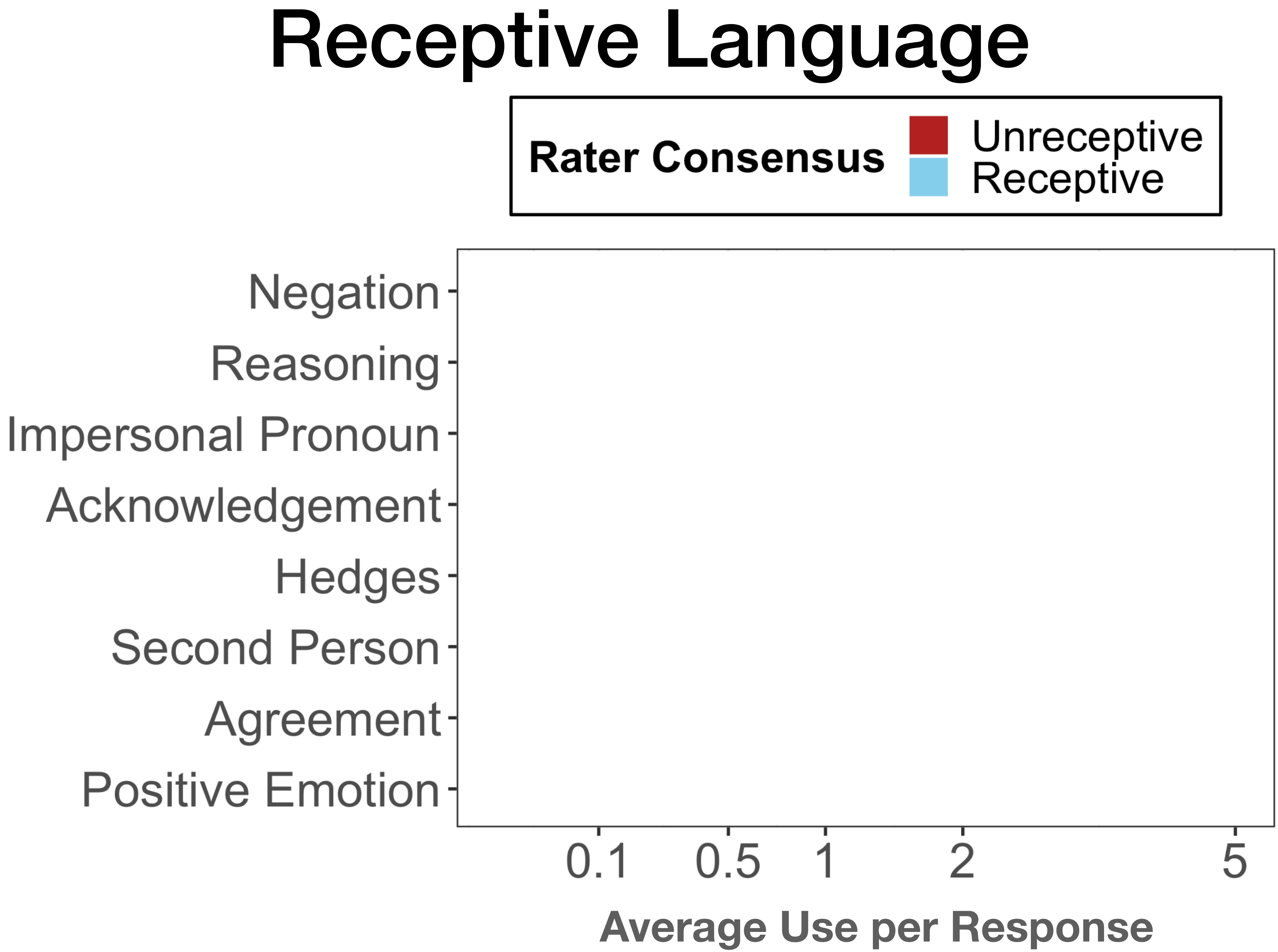
Agreement with Average Judges



Receptive Language

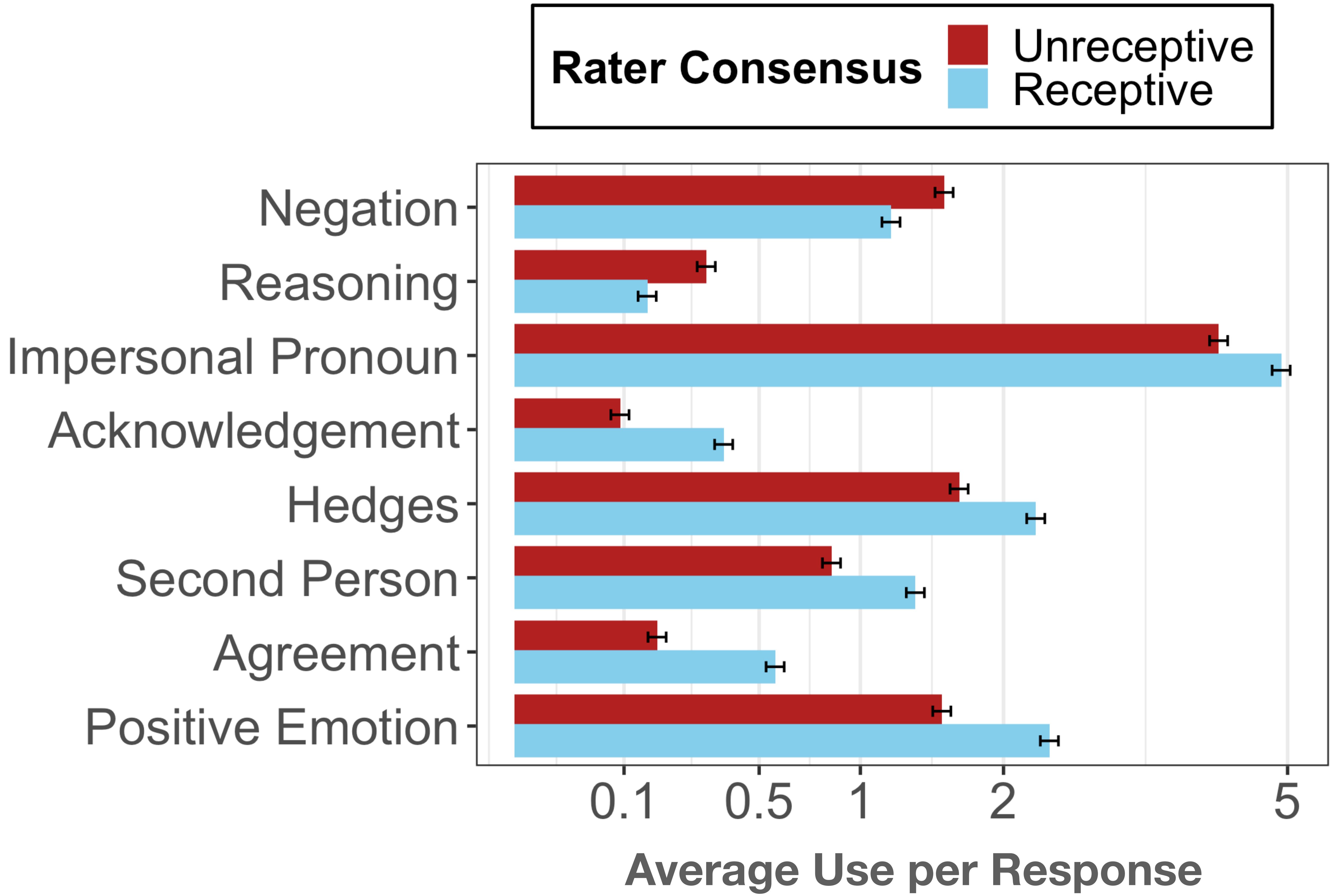
Receptive Language



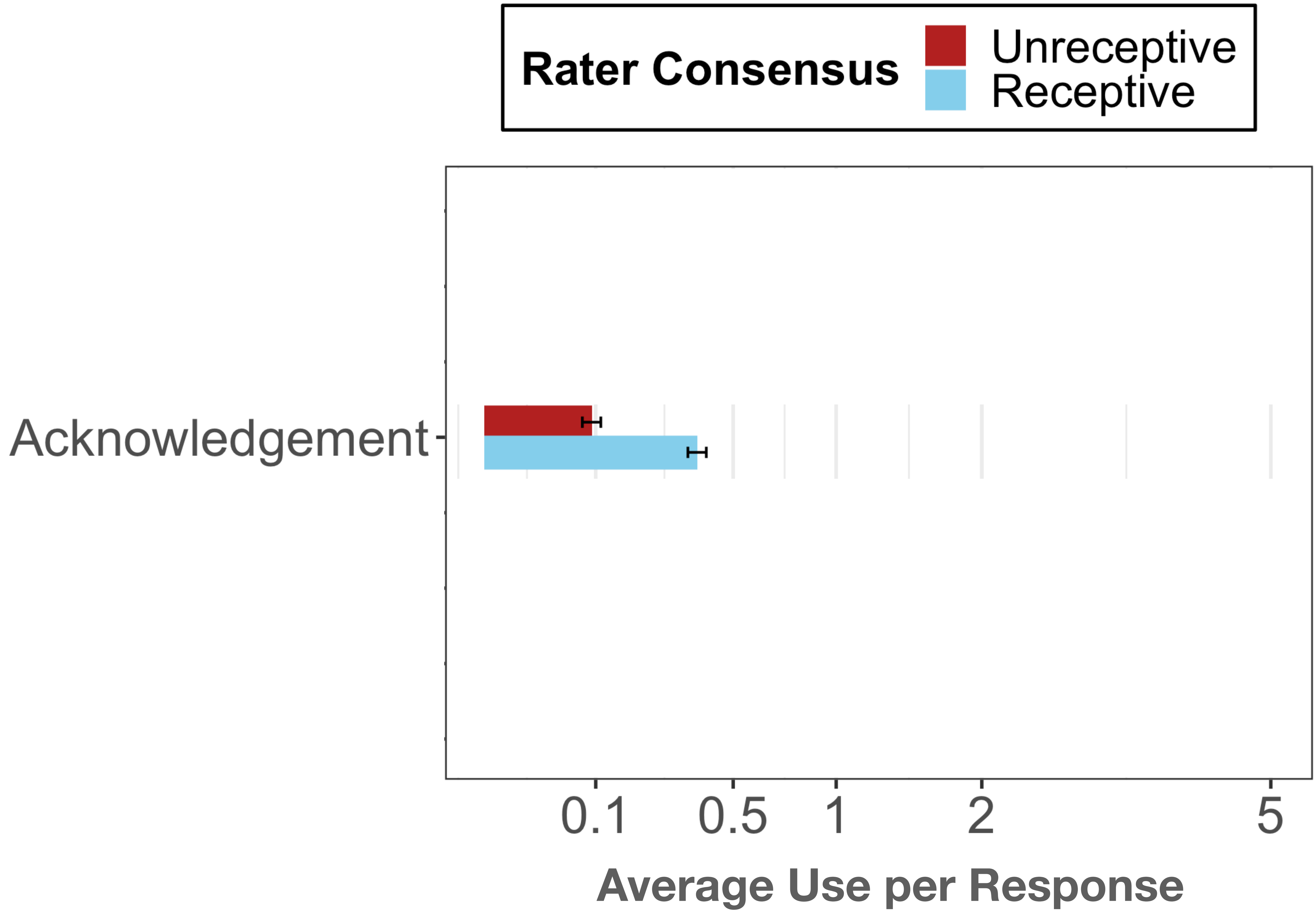


Receptive Language
Rater Consensus
Unreceptive
Receptive
Negation
Reasoning
Impersonal Pronoun
Acknowledgement
Hedges
Second Person
Agreement
Positive Emotion
0.1
0.5
1
2
5
Average Use per Response

Receptive Language



Receptive Language



Receptive Language

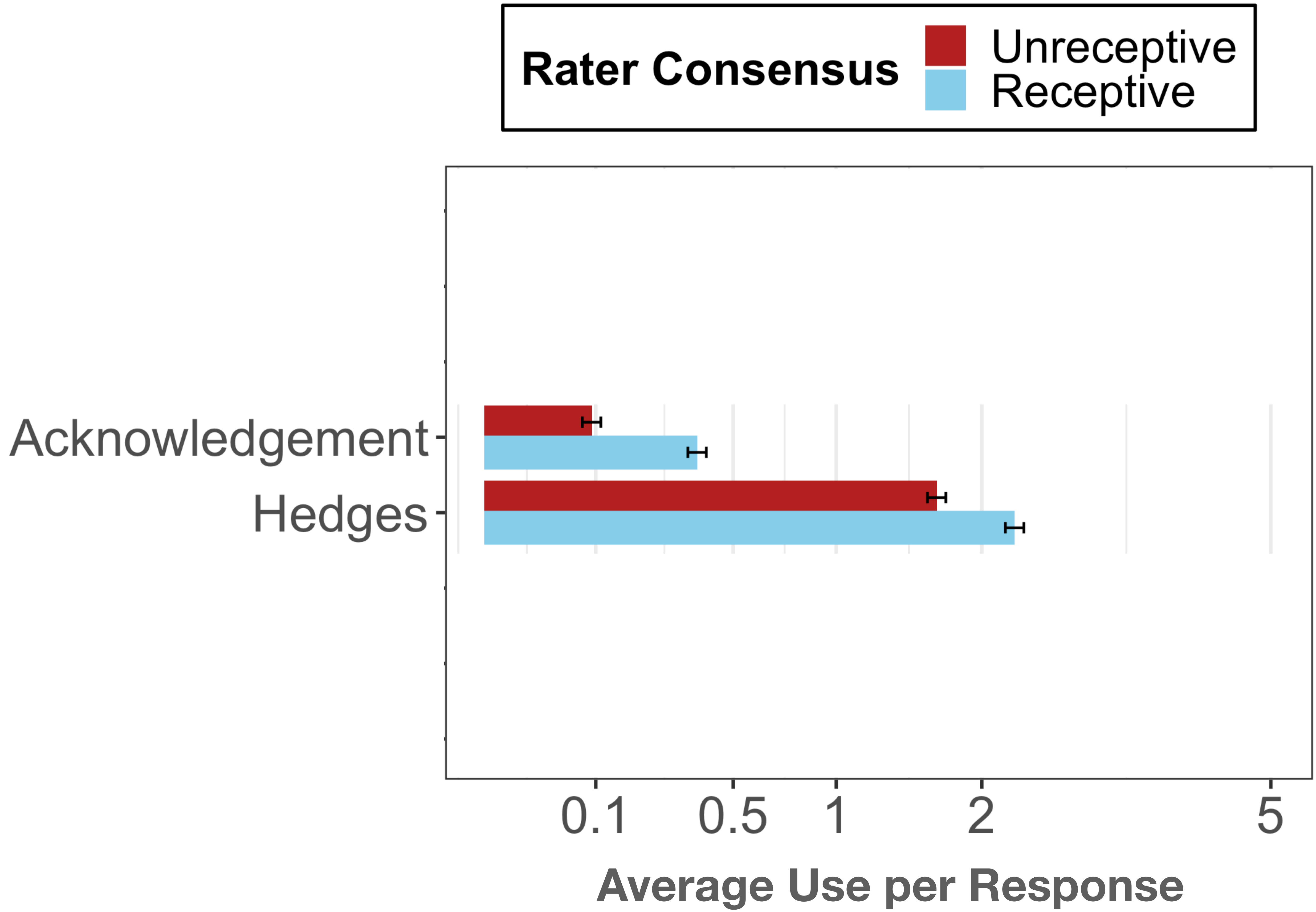
I understand what you are saying. There probably is some truth to the fact that these issues have been hidden for a long time. However, coming from St. Louis and witnessing the Ferguson riots, I can also see how things can be blown out of proportion and make people feel that it is worse than it is. I agree real problems exist, but possibly sometimes attention is drawn in the wrong places.

Receptive Language

I understand what you are saying. There probably is some truth to the fact that these issues have been hidden for a long time. However, coming from St. Louis and witnessing the Ferguson riots, I can also see how things can be blown out of proportion and make people feel that it is worse than it is. I agree real problems exist, but possibly sometimes attention is drawn in the wrong places.

Acknowledgement

Receptive Language



Receptive Language

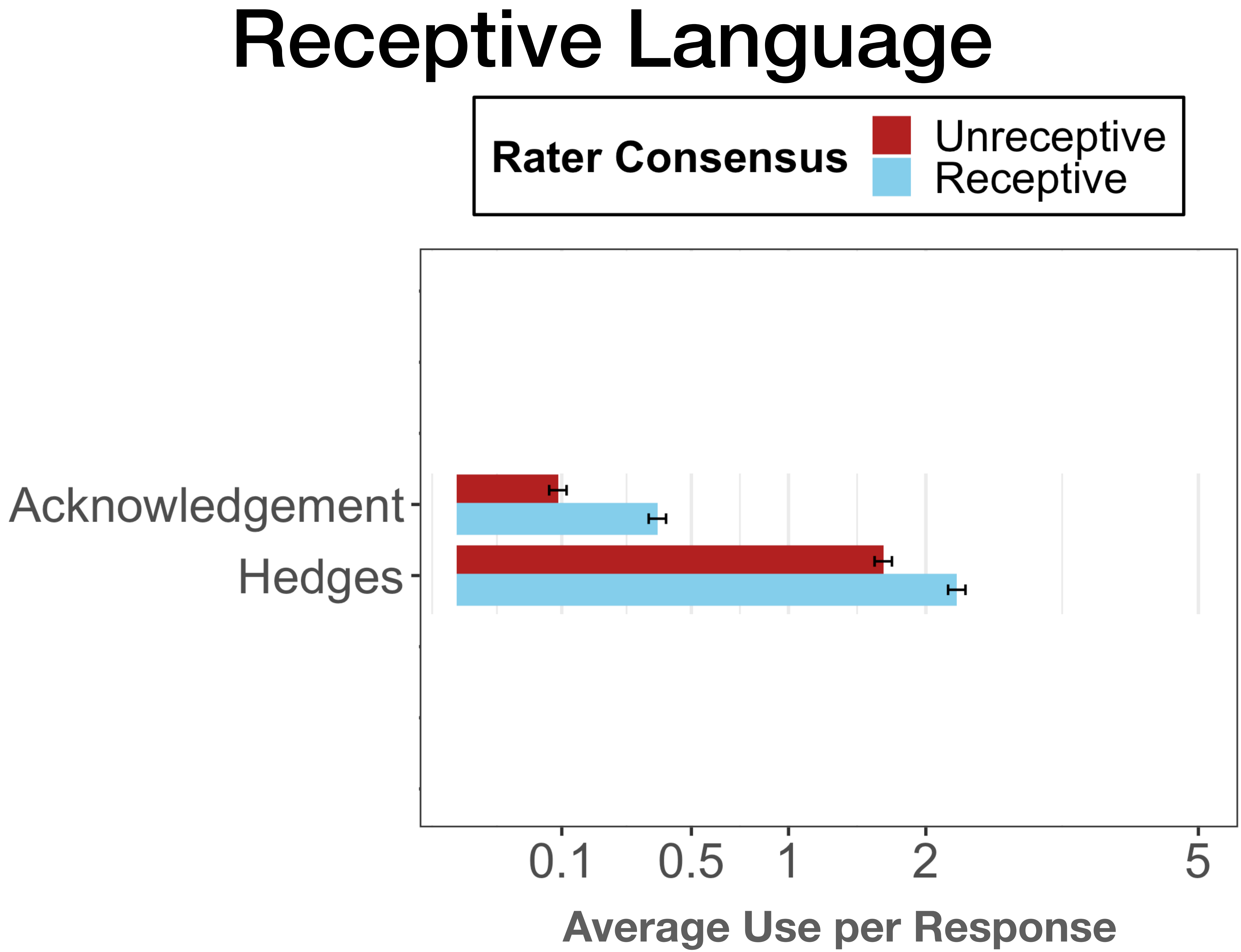
I understand what you are saying. There probably is some truth to the fact that these issues have been hidden for a long time. However, coming from St. Louis and witnessing the Ferguson riots, I can also see how things can be blown out of proportion and make people feel that it is worse than it is. I agree real problems exist, but possibly sometimes attention is drawn in the wrong places.

Hedges

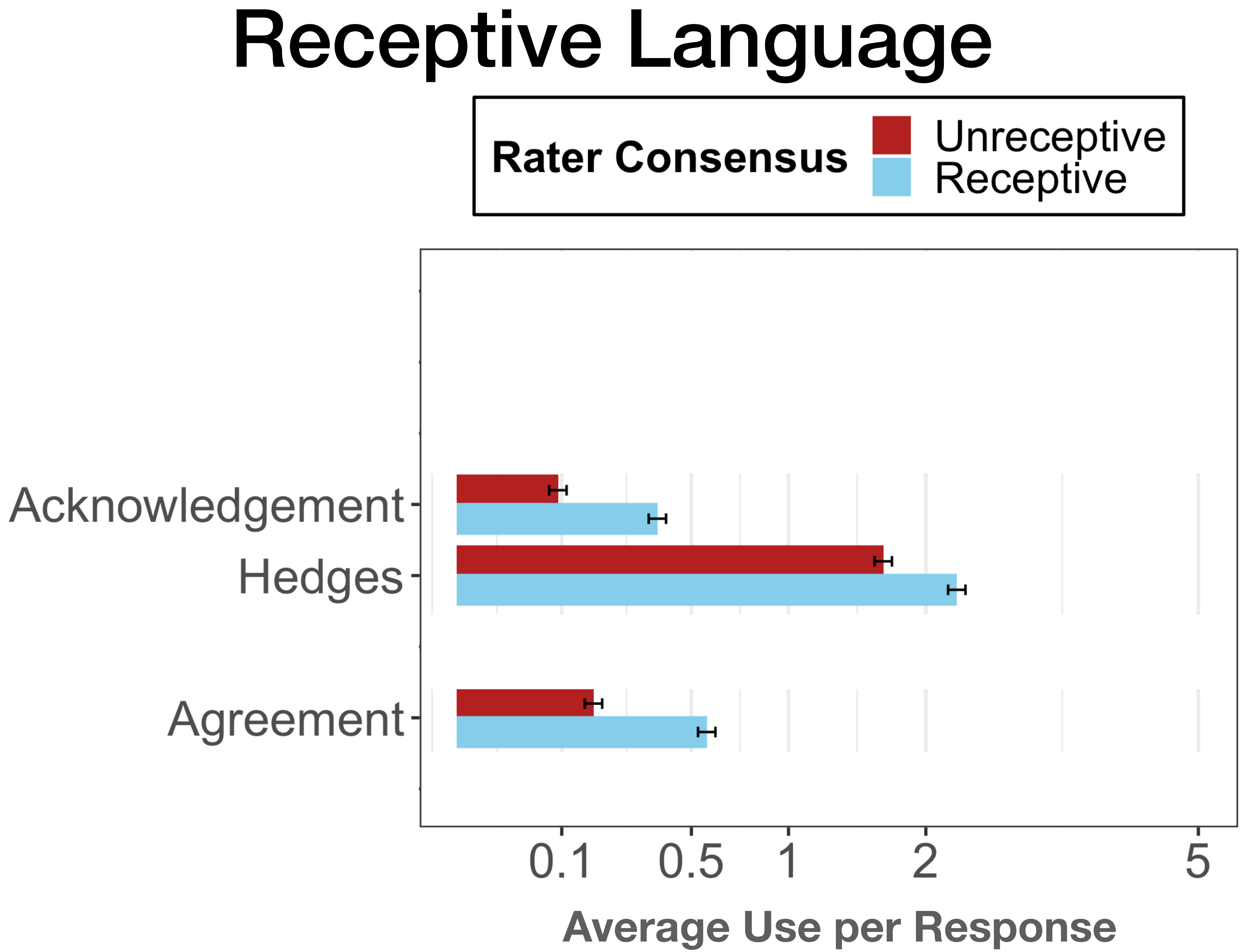
Receptive Language

I understand what you are saying. There probably is some truth to the fact that these issues have been hidden for a long time. However, coming from St. Louis and witnessing the Ferguson riots, I can also see how things can be blown out of proportion and make people feel that it is worse than it is. I agree real problems exist, but possibly sometimes attention is drawn in the wrong places.

Hedges



Receptive Language
Rater Consensus
Unreceptive
Receptive
Acknowledgement
Hedges
0.1
0.5
1
2
5
Average Use per Response



Receptive Language
Rater Consensus
Unreceptive
Receptive
Acknowledgement
Hedges
Agreement
0.1
0.5
1
2
5
Average Use per Response

Receptive Language

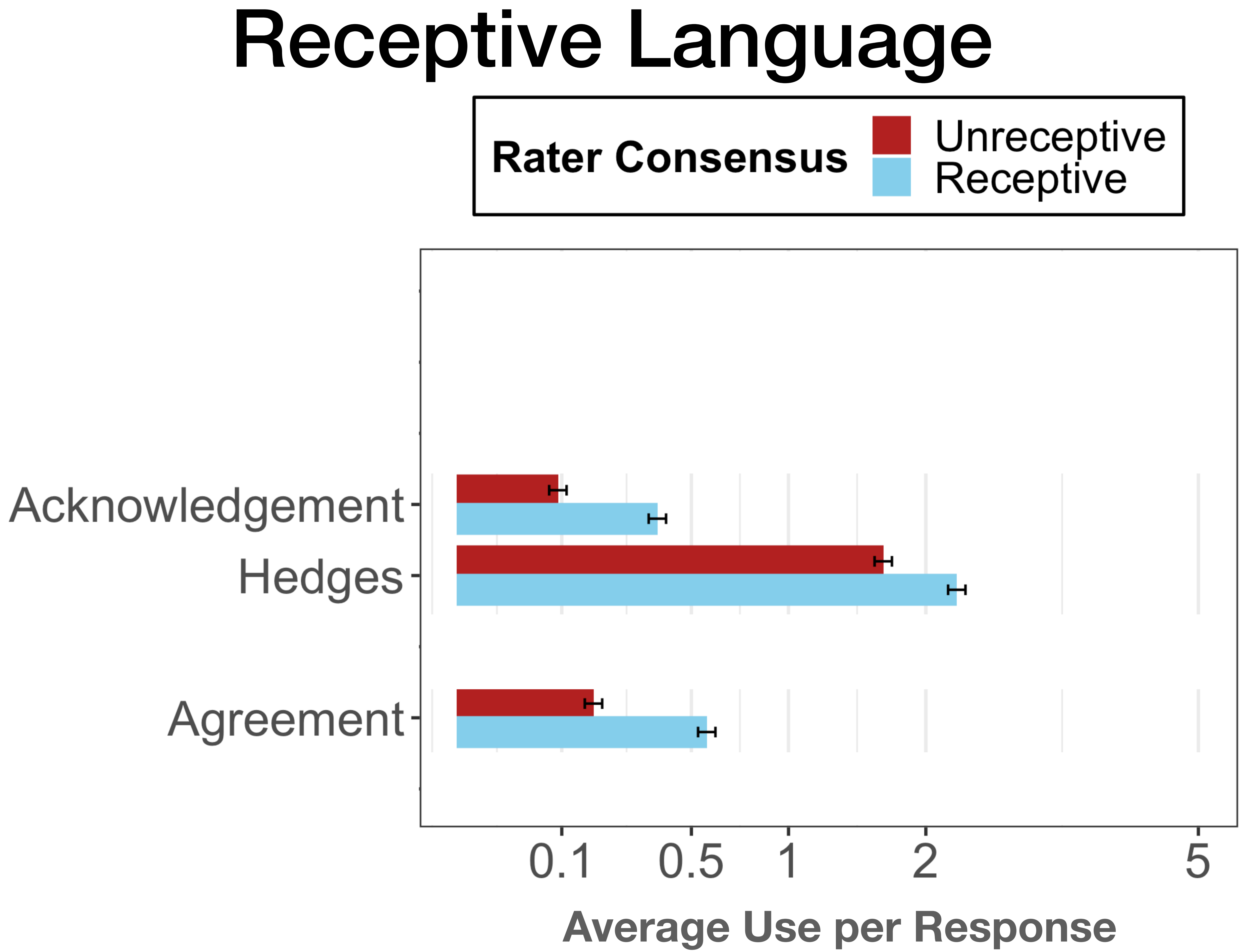
I understand what you are saying. There probably is some truth to the fact that these issues have been hidden for a long time. However, coming from St. Louis and witnessing the Ferguson riots, I can also see how things can be blown out of proportion and make people feel that it is worse than it is. I agree real problems exist, but possibly sometimes attention is drawn in the wrong places.

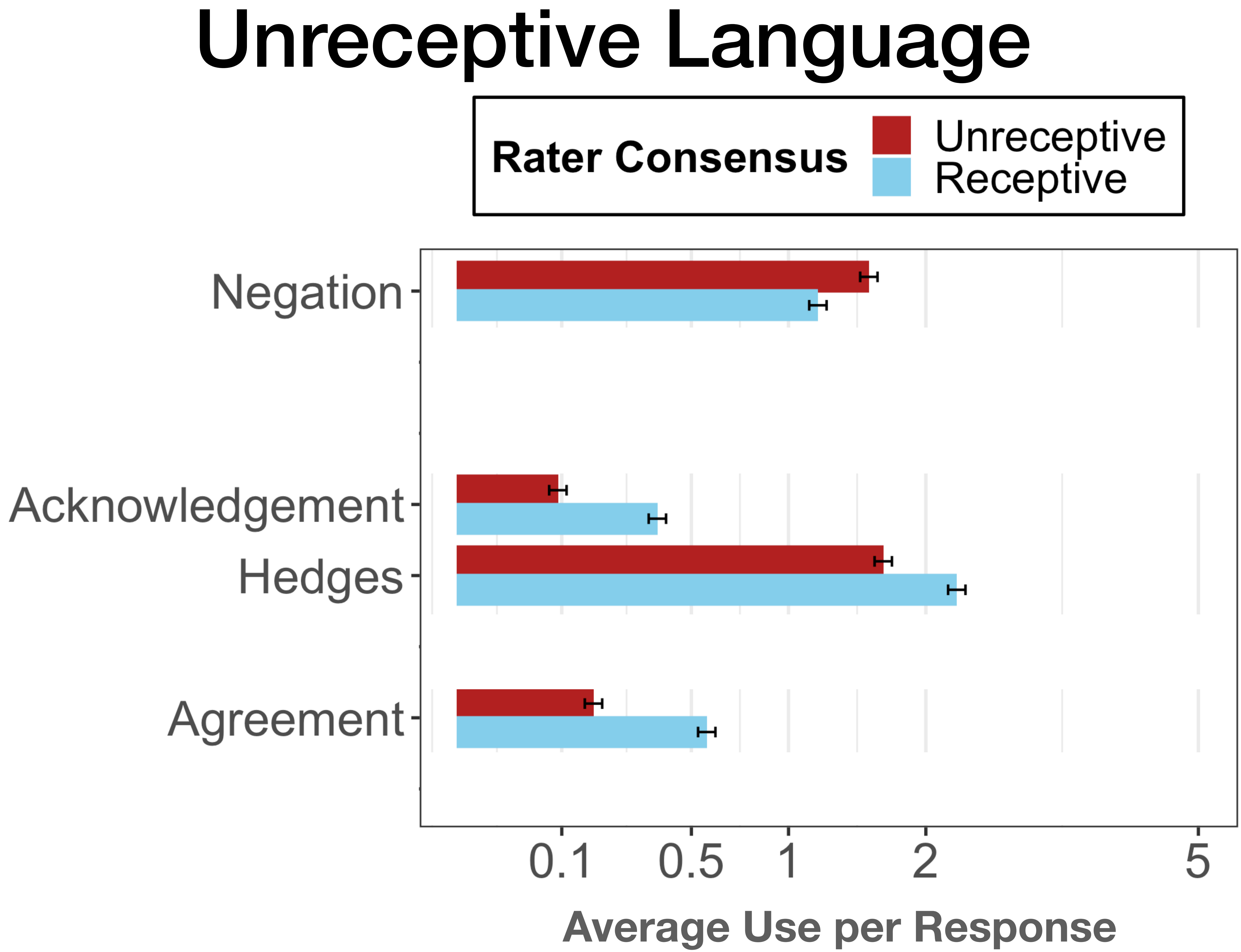
Agreement

Receptive Language

I understand what you are saying. There probably is some truth to the fact that these issues have been hidden for a long time. However, coming from St. Louis and witnessing the Ferguson riots, I can also see how things can be blown out of proportion and make people feel that it is worse than it is. I agree real problems exist, but possibly sometimes attention is drawn in the wrong places.

Agreement


Receptive Language
Rater Consensus
Unreceptive
Receptive
Acknowledgement
Hedges
Agreement
0.1
0.5
1
2
5
Average Use per Response


Unreceptive Language
Rater Consensus
Unreceptive
Receptive
Negation
Acknowledgement
Hedges
Agreement
0.1
0.5
1
2
5
Average Use per Response

Unreceptive Language

Over-reacting to police confrontations, can be deadly to the public in general. When animosity towards the police rises, as it has in Chicago, police do not feel safe, going into the ghetto neighborhoods. Therefore those people, in those neighborhood, literally, have to fend for themselves, because if they need the police and call for their help, the police can't help those in need there, because they will likely be shot at themselves.

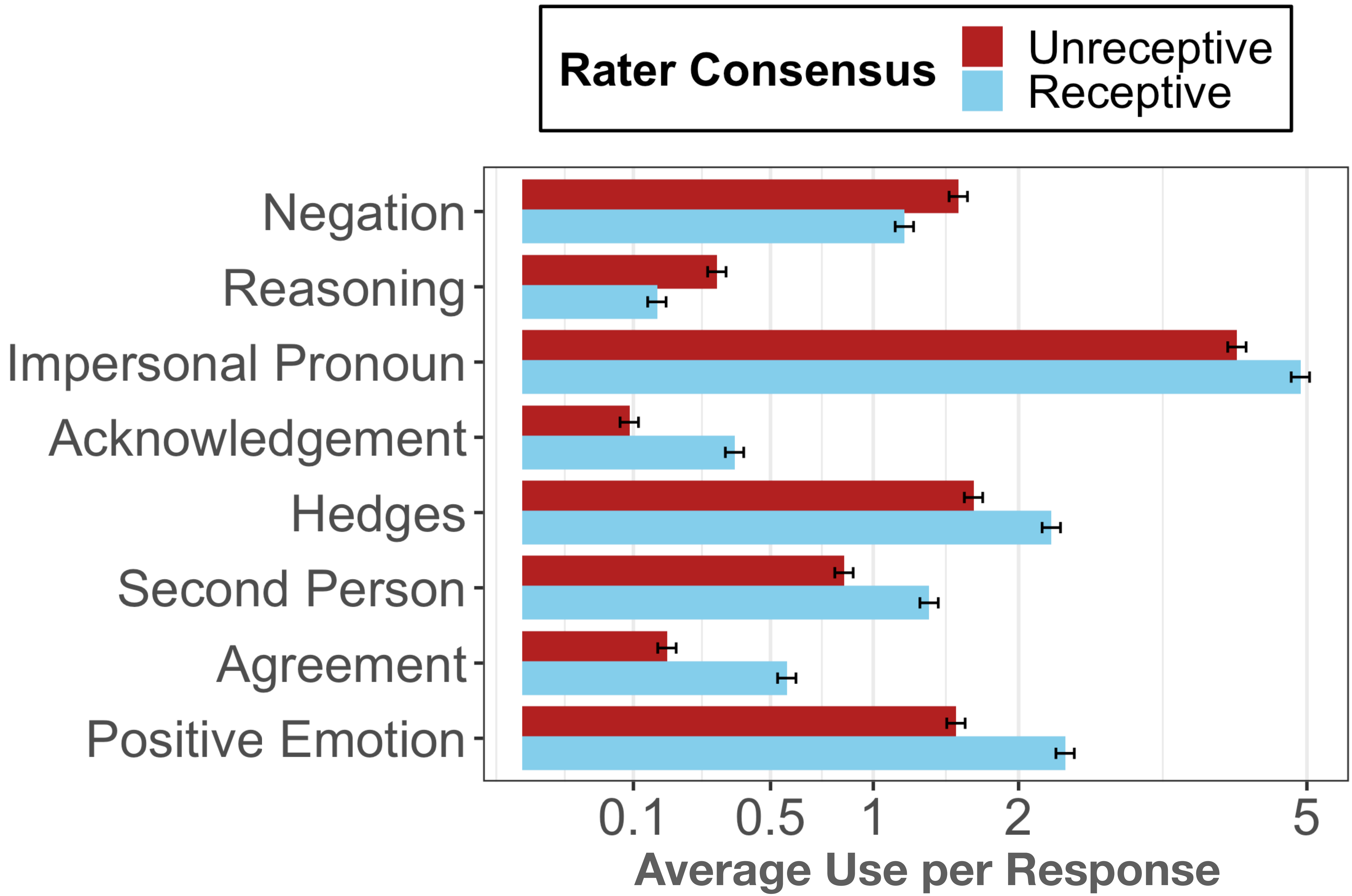
Negation

Unreceptive Language

Over-reacting to police confrontations, can be deadly to the public in general. When animosity towards the police rises, as it has in Chicago, police do not feel safe, going into the ghetto neighborhoods. Therefore those people, in those neighborhood, literally, have to fend for themselves, because if they need the police and call for their help, the police can't help those in need there, because they will likely be shot at themselves.

Negation

The Receptiveness Detector



Back to the Cloud...

Conversational Receptiveness

...is measurable from behavioral data

Study 1 - Mechanical Turk

...improves the health of conversations

Study 2 - HarvardX Online Courses

Study 3 - Wikipedia Editors

...is misunderstood by people in conflict

Study 4 - Local Government Officials

Study 5 - The Receptiveness Recipe

Conversational Receptiveness

...is measurable from behavioral data

Study 1 - Mechanical Turk

✓

...improves the health of conversations

Study 2 - HarvardX Online Courses

Study 3 - Wikipedia Editors

...is misunderstood by people in conflict

Study 4 - Local Government Officials

Study 5 - The Receptiveness Recipe

Conversational Receptiveness

...is measurable from behavioral data

Study 1 - Mechanical Turk

...improves the health of conversations

Study 2 - HarvardX Online Courses

Study 3 - Wikipedia Editors

...is misunderstood by people in conflict

Study 4 - Local Government Officials

Study 5 - The Receptiveness Recipe

Conversational Receptiveness

...is measurable from behavioral data

Study 1 - Mechanical Turk

...improves the health of conversations

Study 2 - HarvardX Online Courses

Study 3 - Wikipedia Editors

...is misunderstood by people in conflict

Study 4 - Local Government Officials

Study 5 - The Receptiveness Recipe

Conversational Receptiveness

...is measurable from behavioral data

Study 1 - Mechanical Turk

...improves the health of conversations

Study 2 - HarvardX Online Courses

Study 3 - Wikipedia Editors

...is misunderstood by people in conflict

Study 4 - Local Government Officials

Study 5 - The Receptiveness Recipe

Local Government Officials

HARVARD Kennedy School
TAUBMAN CENTER
for State and Local Government

Local Government Officials

238 Mayors, Attorneys General, Police Chiefs, etc

Executive education program

HARVARD Kennedy School
TAUBMAN CENTER
for State and Local Government

Local Government Officials

238 Mayors, Attorneys General, Police Chiefs, etc

Executive education program

Day 1: pre-survey

Issue positions, own receptiveness

HARVARD Kennedy School
TAUBMAN CENTER
for State and Local Government

Local Government Officials

238 Mayors, Attorneys General, Police Chiefs, etc

Executive education program

Day 1: pre-survey

Issue positions, own receptiveness

Day 2: conversation

Text chat with disagreeing student (anonymous)

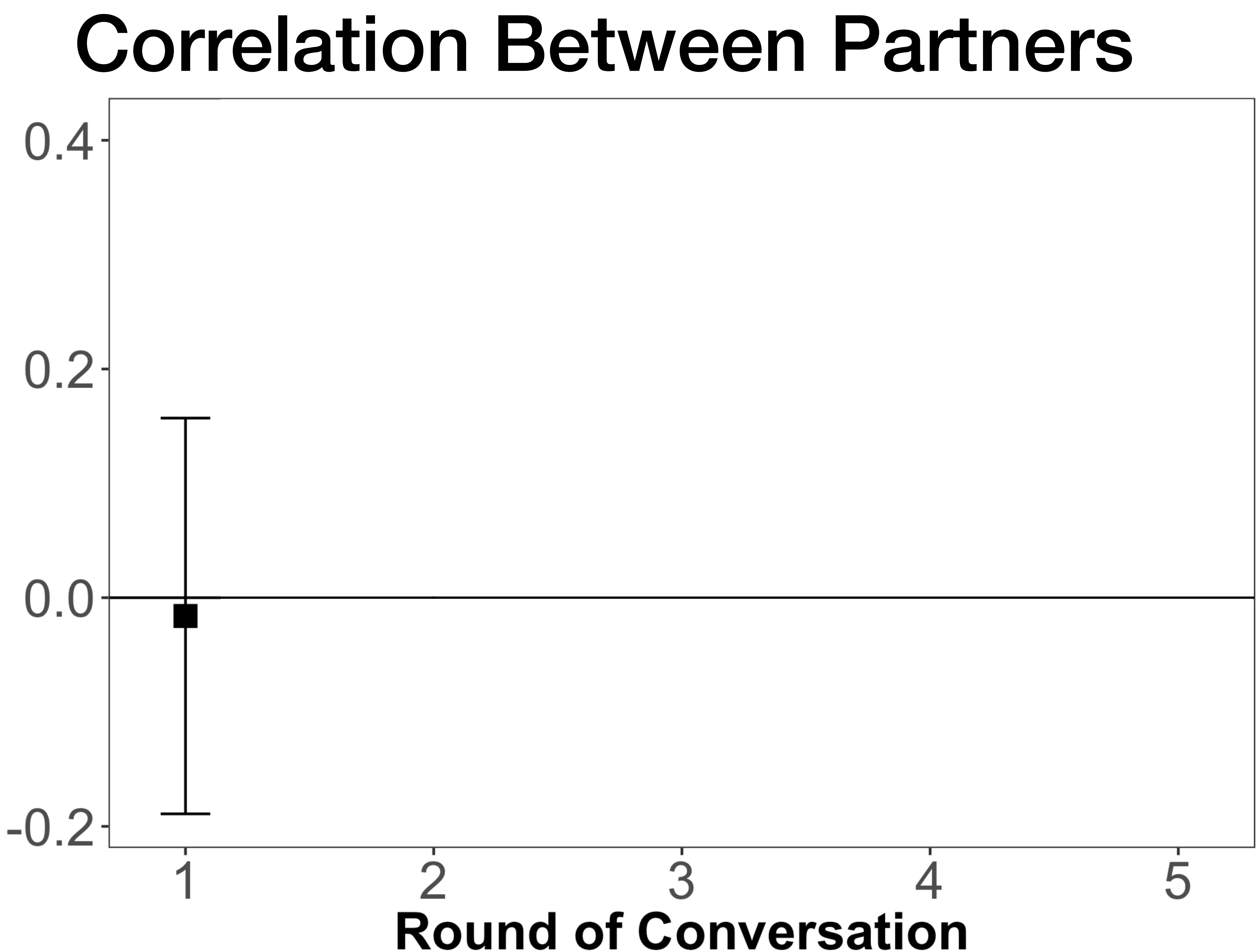
Rate receptiveness of partner & self

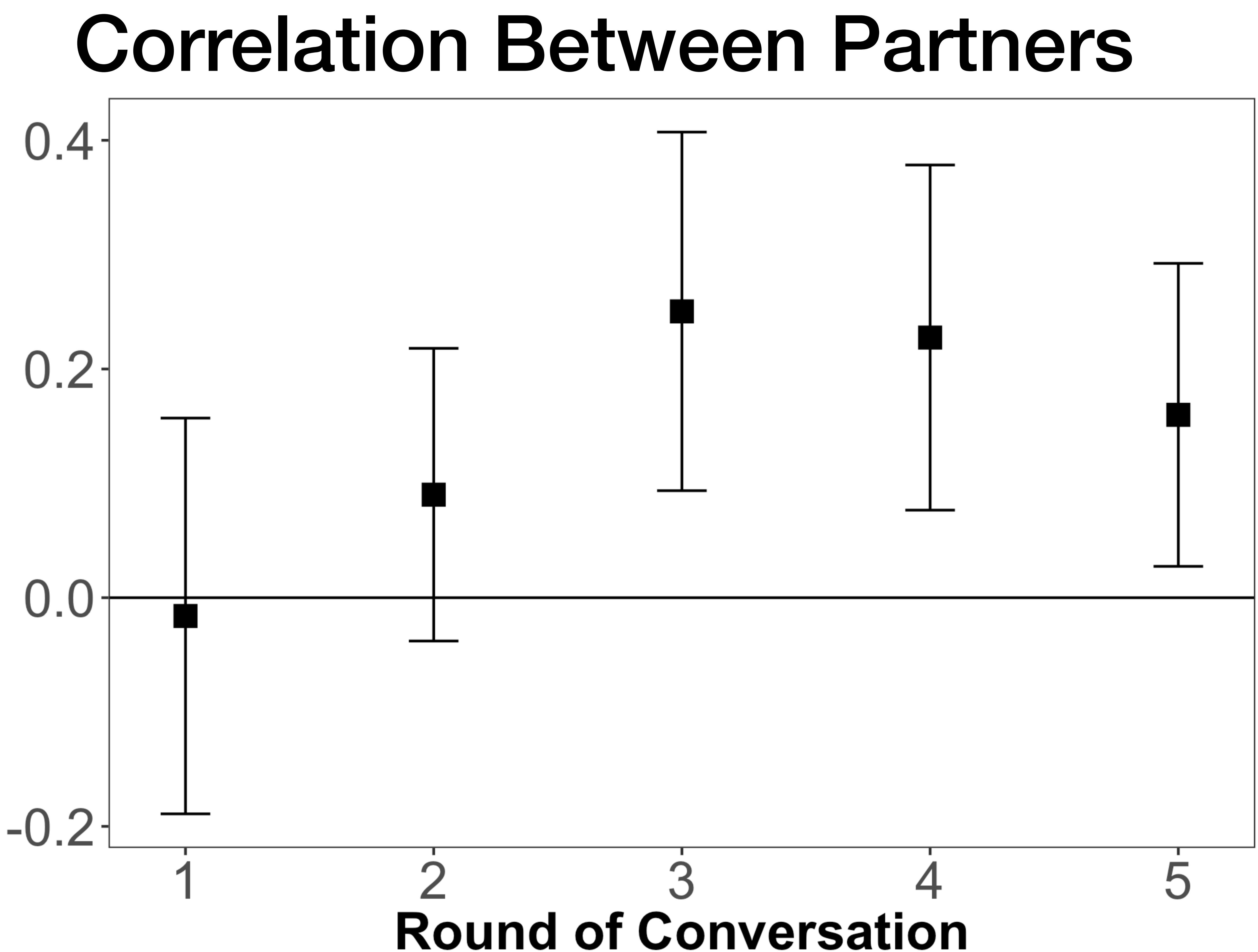
Interpersonal outcomes

HARVARD Kennedy School

TAUBMAN CENTER

for State and Local Government


Correlation Between Partners
0.4
0.2
0.0
-0.2
1
2
3
4
5
Round of Conversation



Correlation Between Partners
0.4
0.2
0.0
-0.2
1
2
3
4
5
Round of Conversation

Back to the Cloud...

RStudio® Cloud

Collaboration Intentions

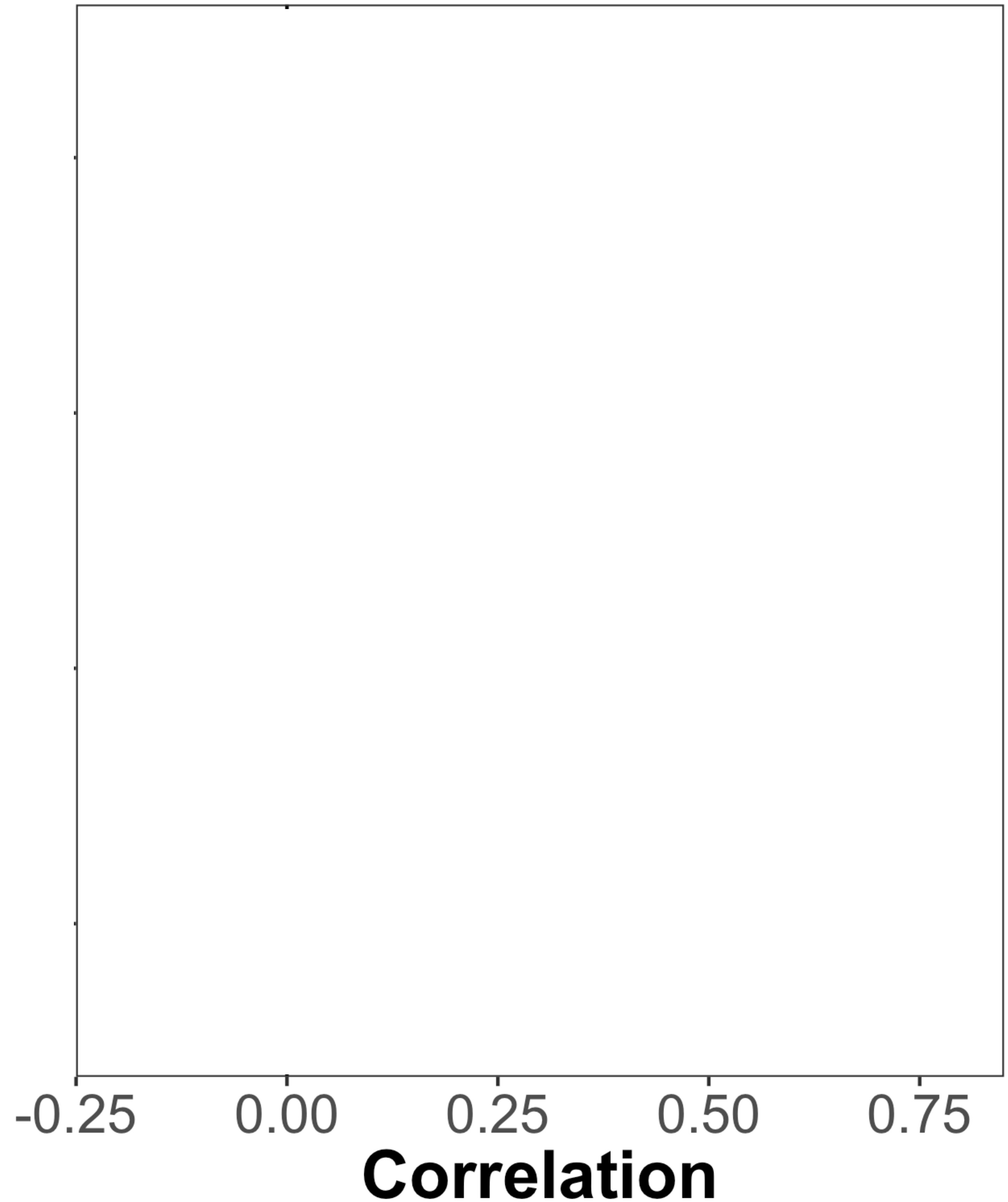
How much do you trust your partner's judgment to make good decisions in complex situations?

How much would you like to have your partner on a work team?

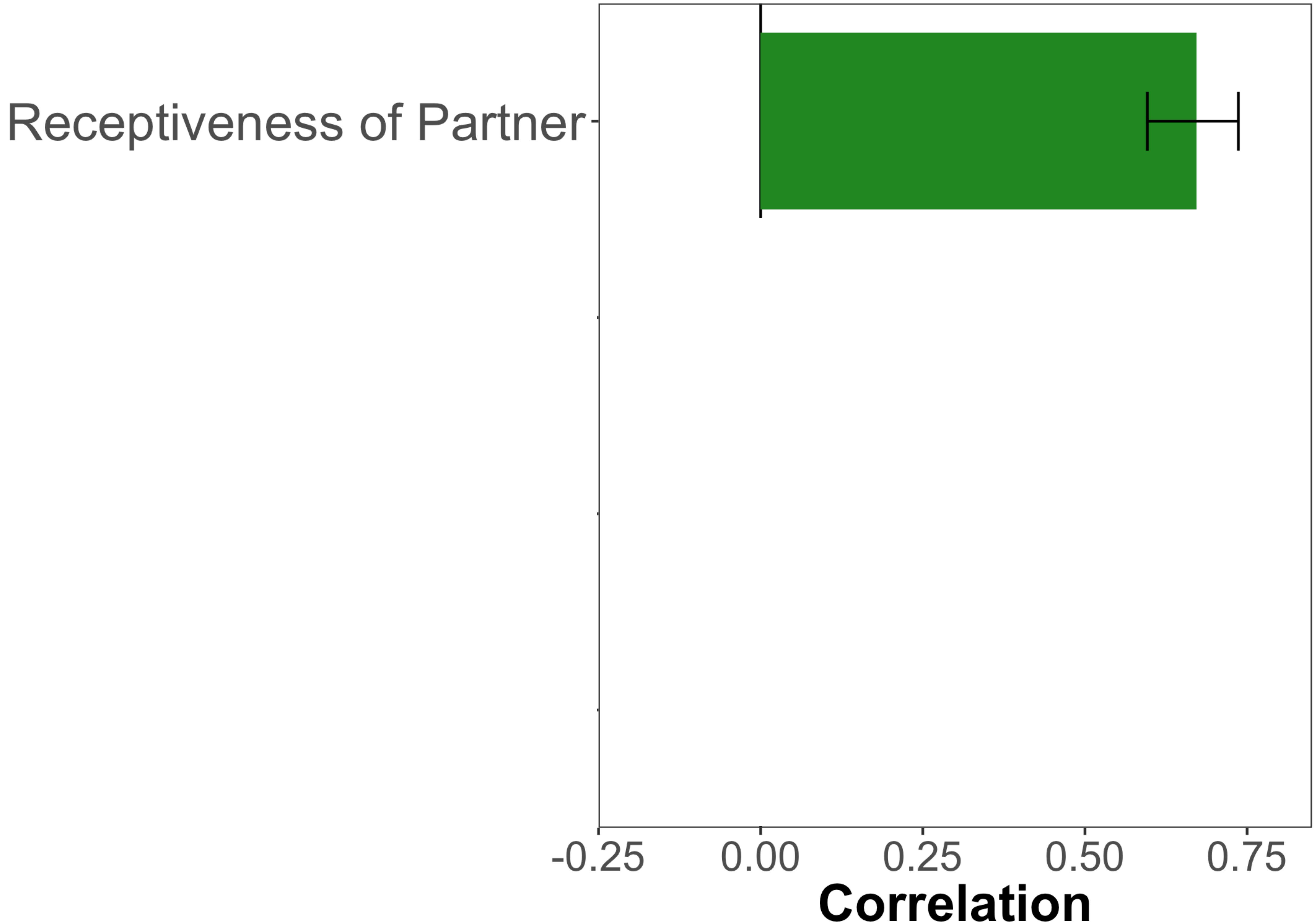
How much would you like your partner to represent you and your organization in a professional context?

($\alpha = 0.85$)

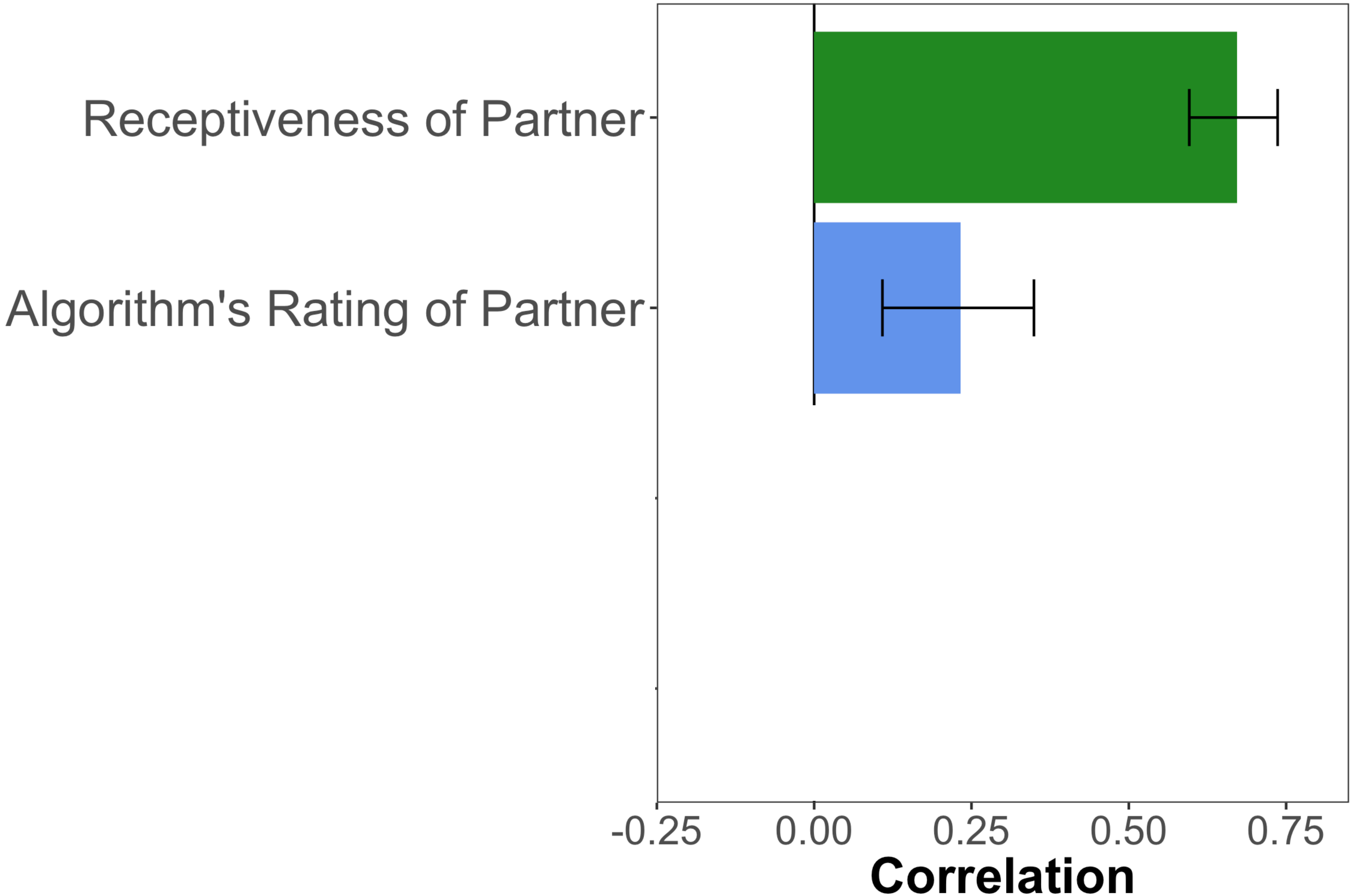
Collaboration Intentions



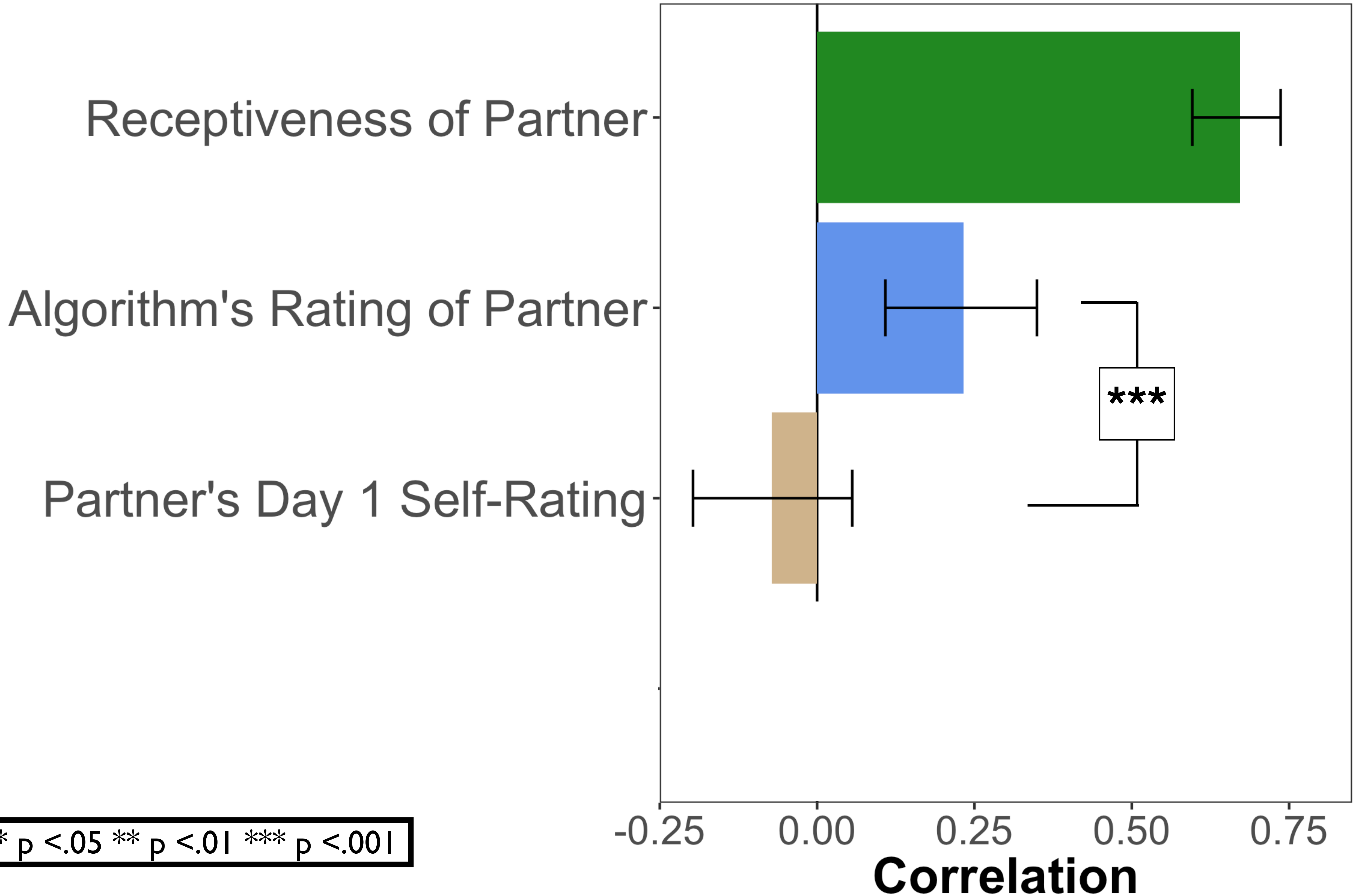
Collaboration Intentions



Collaboration Intentions

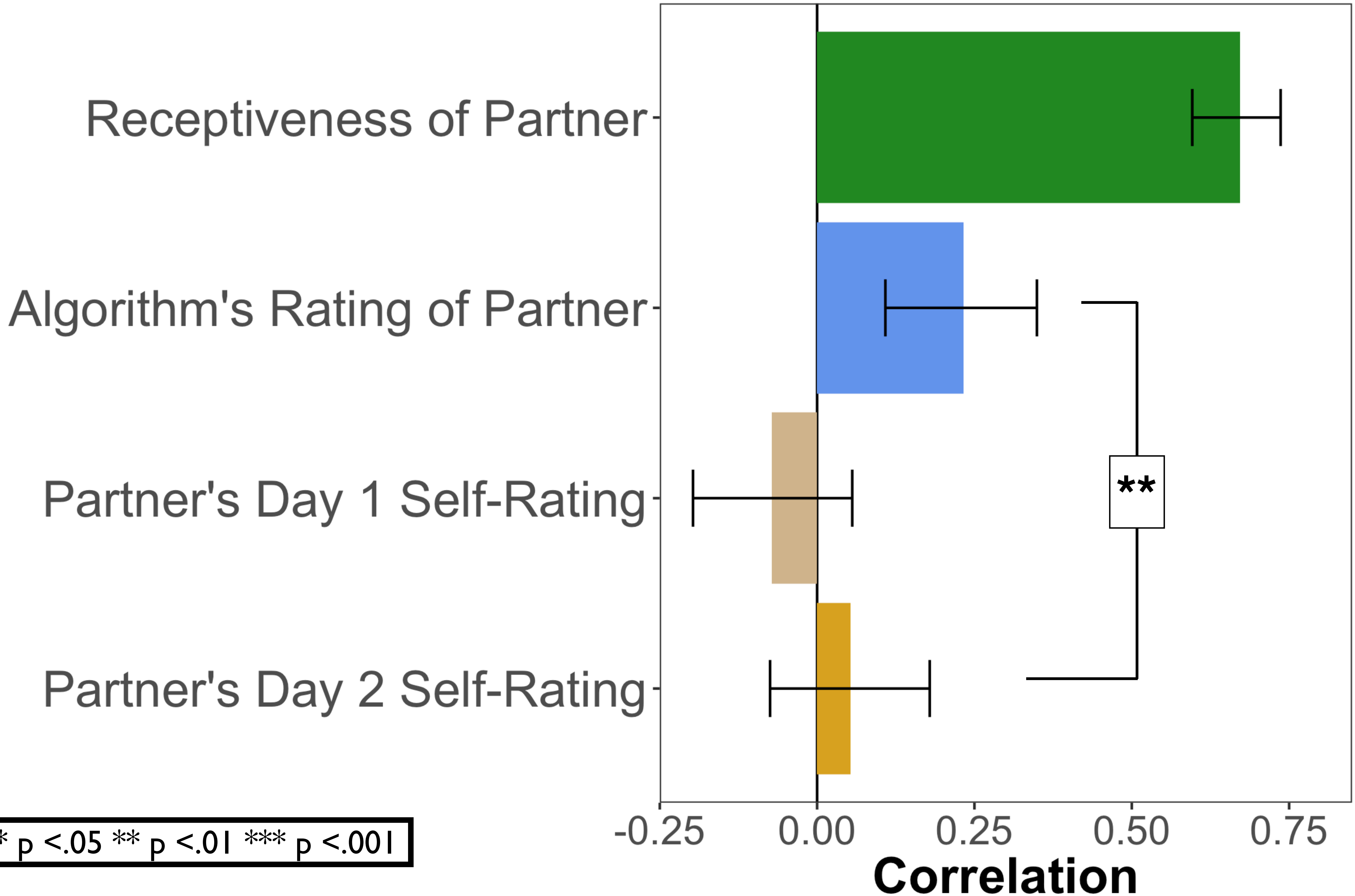


Collaboration Intentions

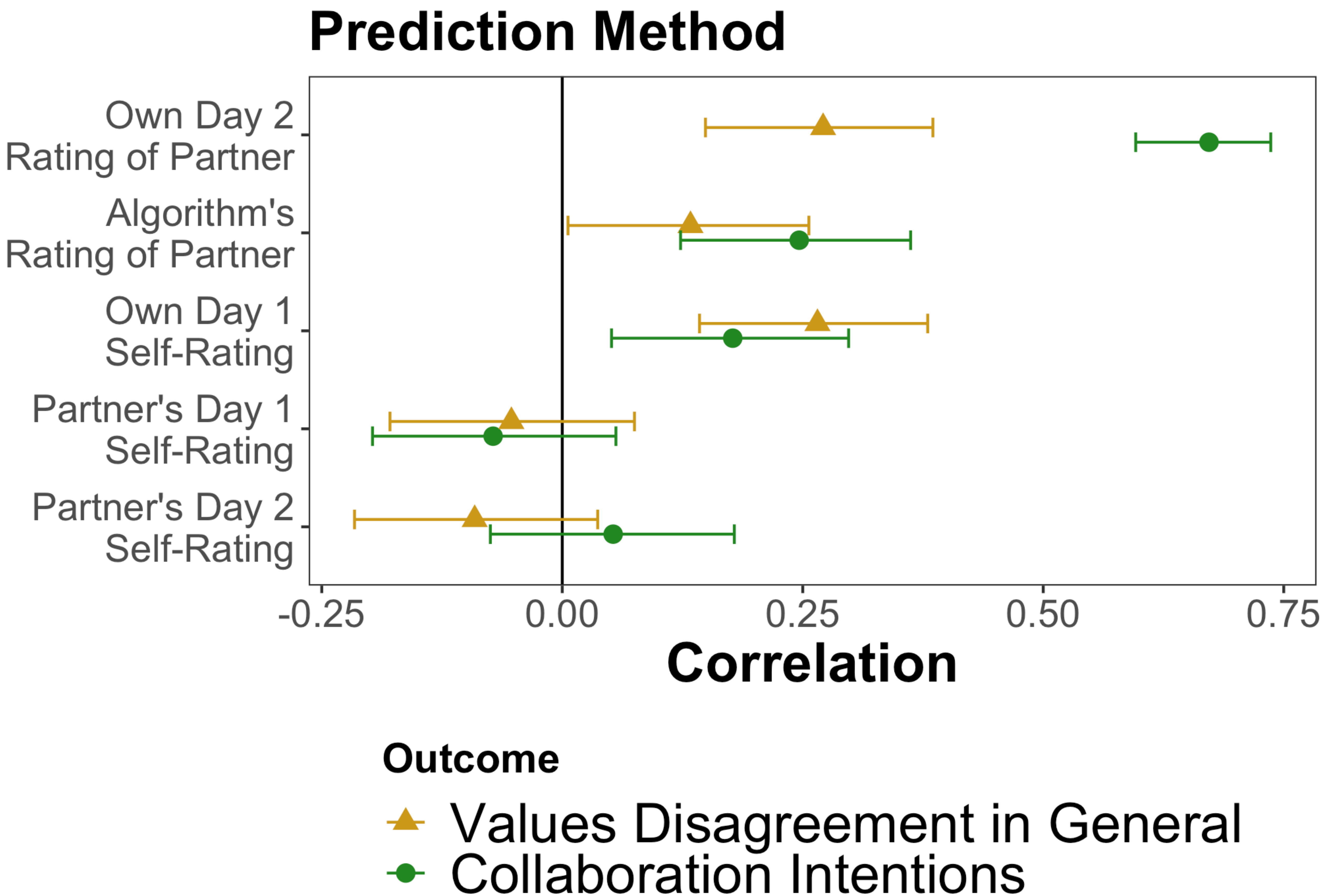


* p <.05 ** p <.01 *** p <.001

Collaboration Intentions



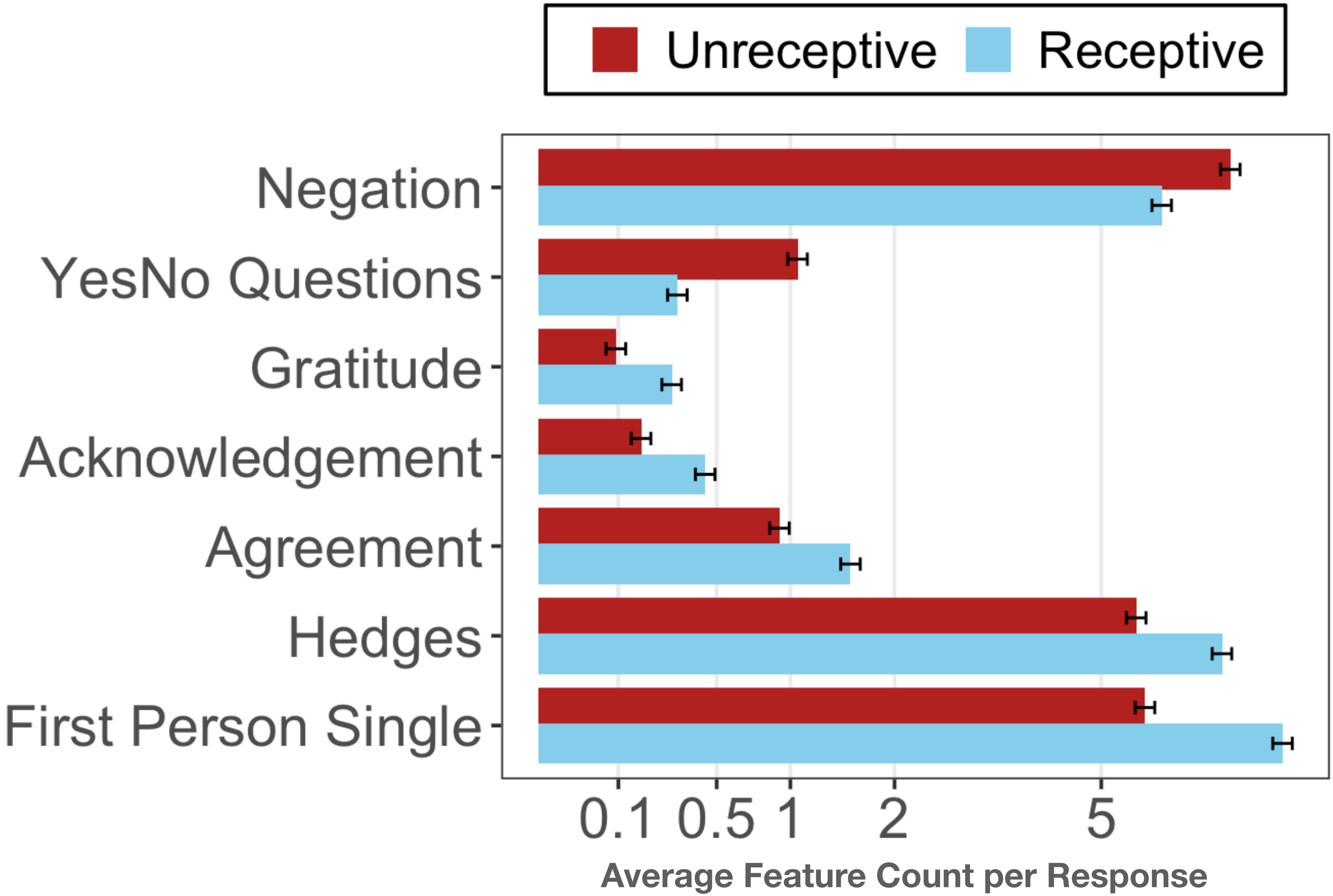
* p <.05 ** p <.01 *** p <.001

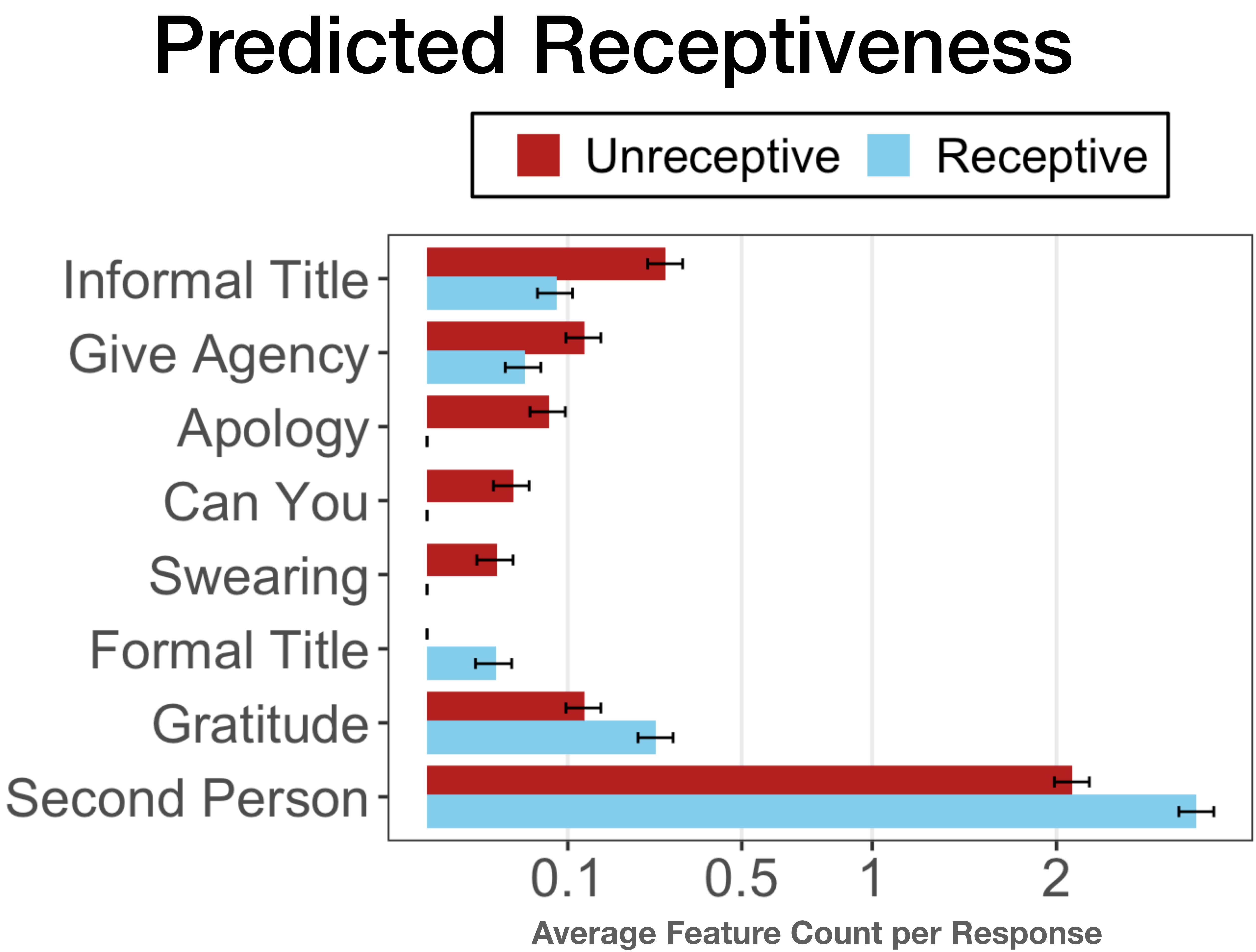


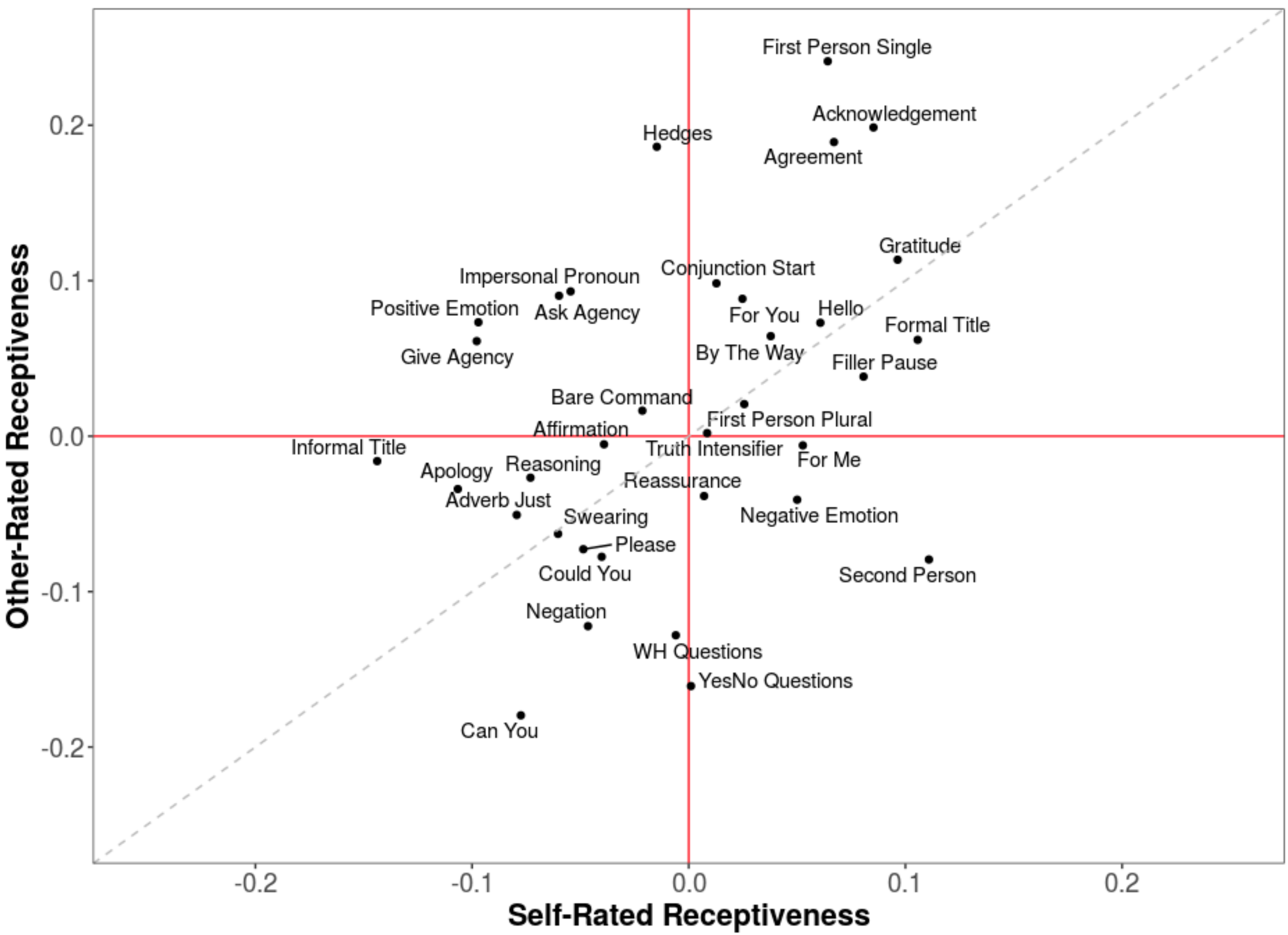
Prediction Method
Own Day 2
Rating of Partner
Algorithm's
Rating of Partner
Own Day 1
Self-Rating
Partner's Day 1
Self-Rating
Partner's Day 2
Self-Rating
-0.25
0.00
0.25
0.50
0.75
Correlation
Outcome
Values Disagreement in General
Collaboration Intentions

Back to the Cloud...

Actual Receptiveness




Predicted Receptiveness
Unreceptive
Receptive
Informal Title
Give Agency
Apology
Can You
Swearing
Formal Title
Gratitude
Second Person
0.1
0.5
1
2
Average Feature Count per Response



First Person Single
Acknowledgement
Hedges
Agreement
Gratitude
Conjunction Start
Impersonal Pronoun
Positive Emotion
Ask Agency
For You
Hello
Formal Title
Give Agency
By The Way
Filler Pause
Bare Command
First Person Plural
Affirmation
Informal Title
Truth Intensifier
For Me
Apology
Reasoning
Reassurance
Adverb Just
Negative Emotion
Swearing
Please
Could You
Second Person
Negation
WH Questions
YesNo Questions
Can You
0.2
0.1
0.0
-0.1
-0.2
Other-Rated Receptiveness
Self-Rated Receptiveness

Conversational Receptiveness

...is measurable from behavioral data

Study 1 - Mechanical Turk

...improves the health of conversations

Study 2 - HarvardX Online Courses

Study 3 - Wikipedia Editors

...is misunderstood by people in conflict

Study 4 - Local Government Officials

Study 5 - The Receptiveness Recipe

Conversational Receptiveness

...is measurable from behavioral data

Study 1 - Mechanical Turk

...improves the health of conversations

Study 2 - HarvardX Online Courses

Study 3 - Wikipedia Editors

...is misunderstood by people in conflict

Study 4 - Local Government Officials

Study 5 - The Receptiveness Recipe

The Receptiveness Recipe

The Receptiveness Recipe

Use positive affirming statements, not contradicting statements.

Acknowledge the other person's views.

Use "hedges" to soften your claims.

Try to find points of agreement.

The Receptiveness Recipe

Use positive affirming statements, not contradicting statements.

For example, you should say: "**X is true**" or "**X is good**",
rather than: "Y is not true"

Acknowledge the other person's views.

Demonstrate your listening by saying things like: "**I see your point,**"
or "**I understand where you are coming from.**"

Use "hedges" to soften your claims.

For example, you could say: "X is **partly true...** "
or " Y is **sometimes the case**"

Try to find points of agreement.

Even when you disagree, it helps to also focus on some things you do agree with,
like "**I agree that it's a difficult situation, which is why X**",
rather than "that doesn't work because Y"

The Receptiveness Recipe

The public reaction to recent confrontations between police and minority crime suspects has been overblown.

Issue Prompt

1 of 2

No, it hasn't!

Position Statement

1 of 20, from old data

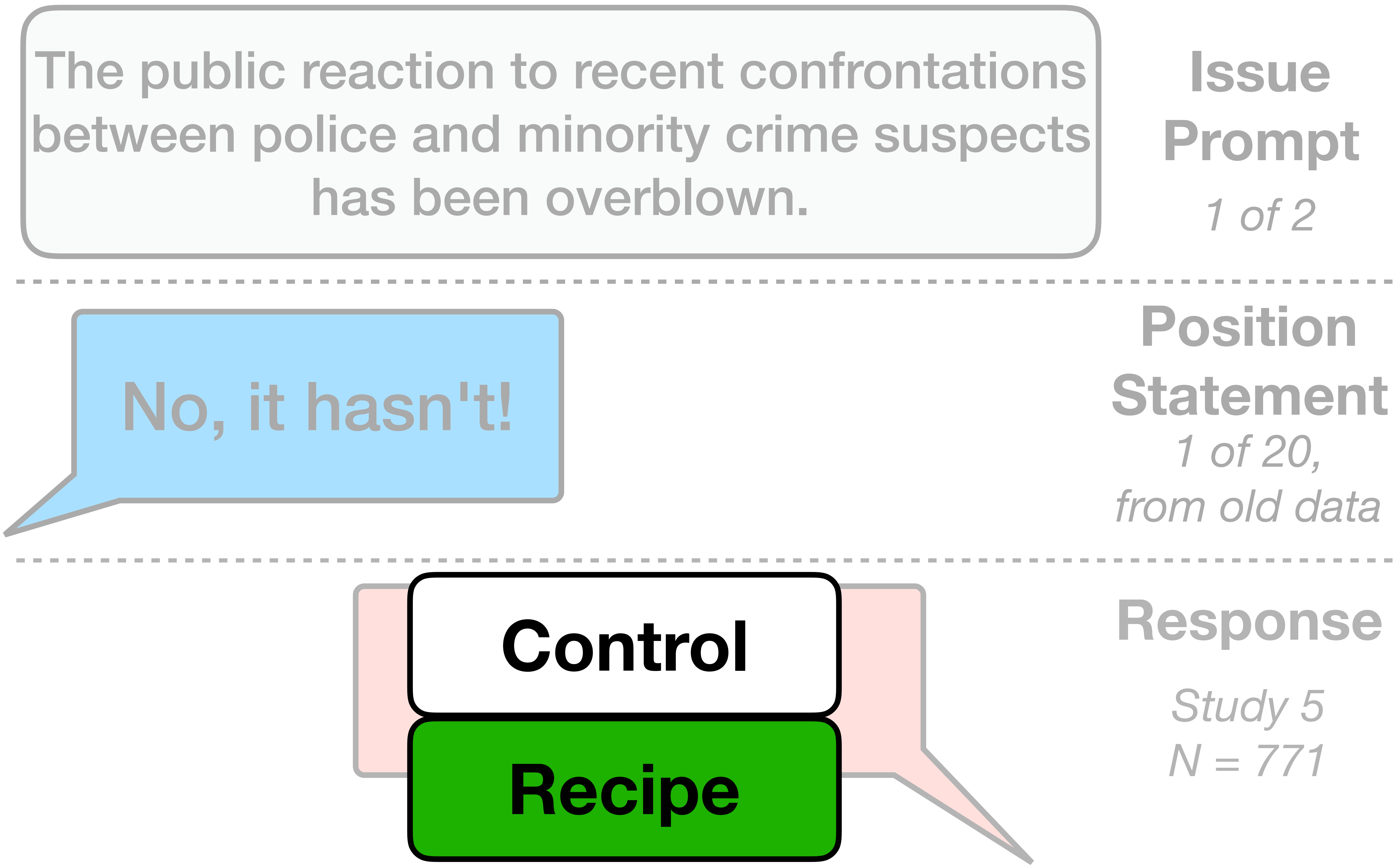
Yes, it has!

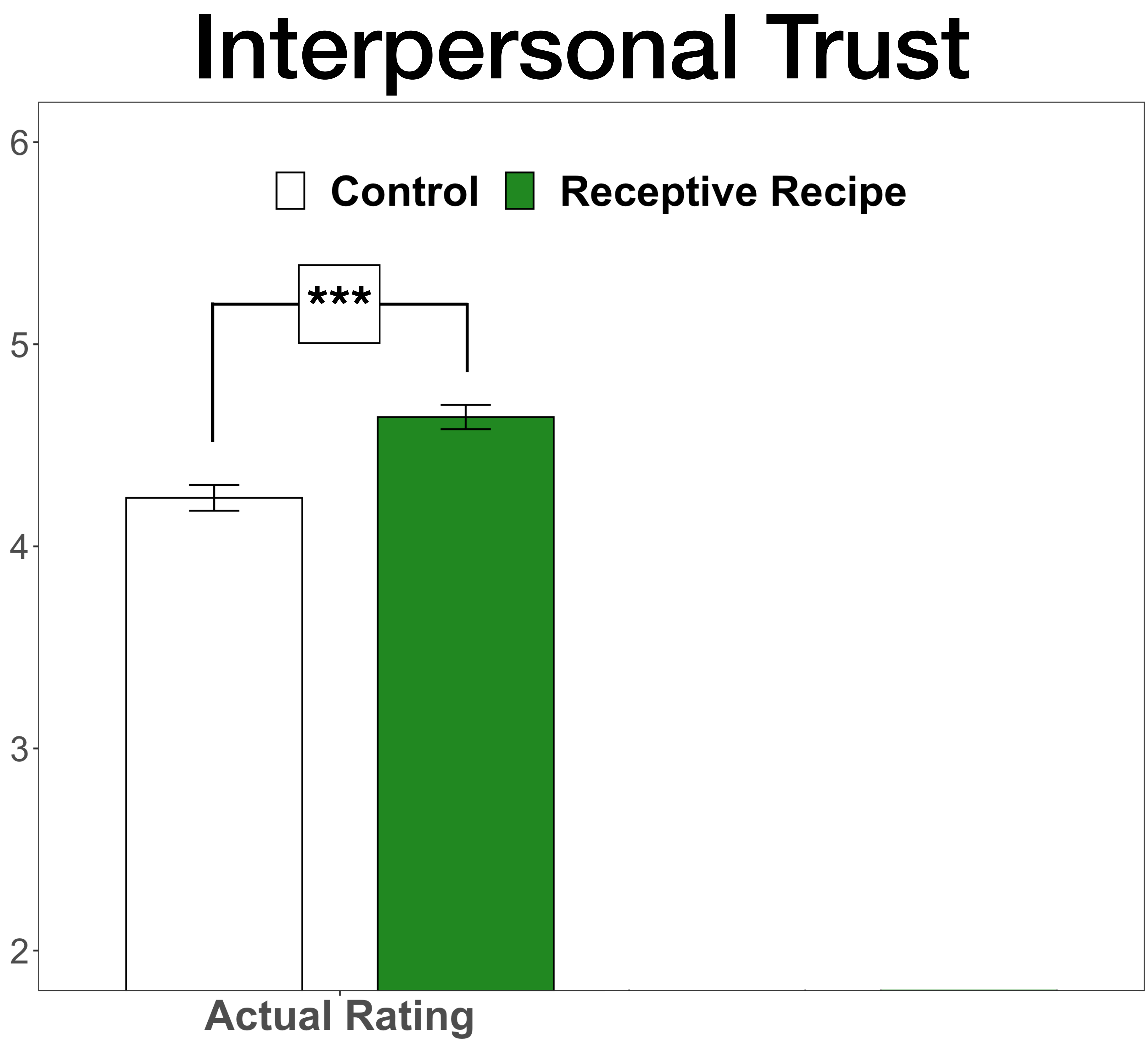
Response

Study 5

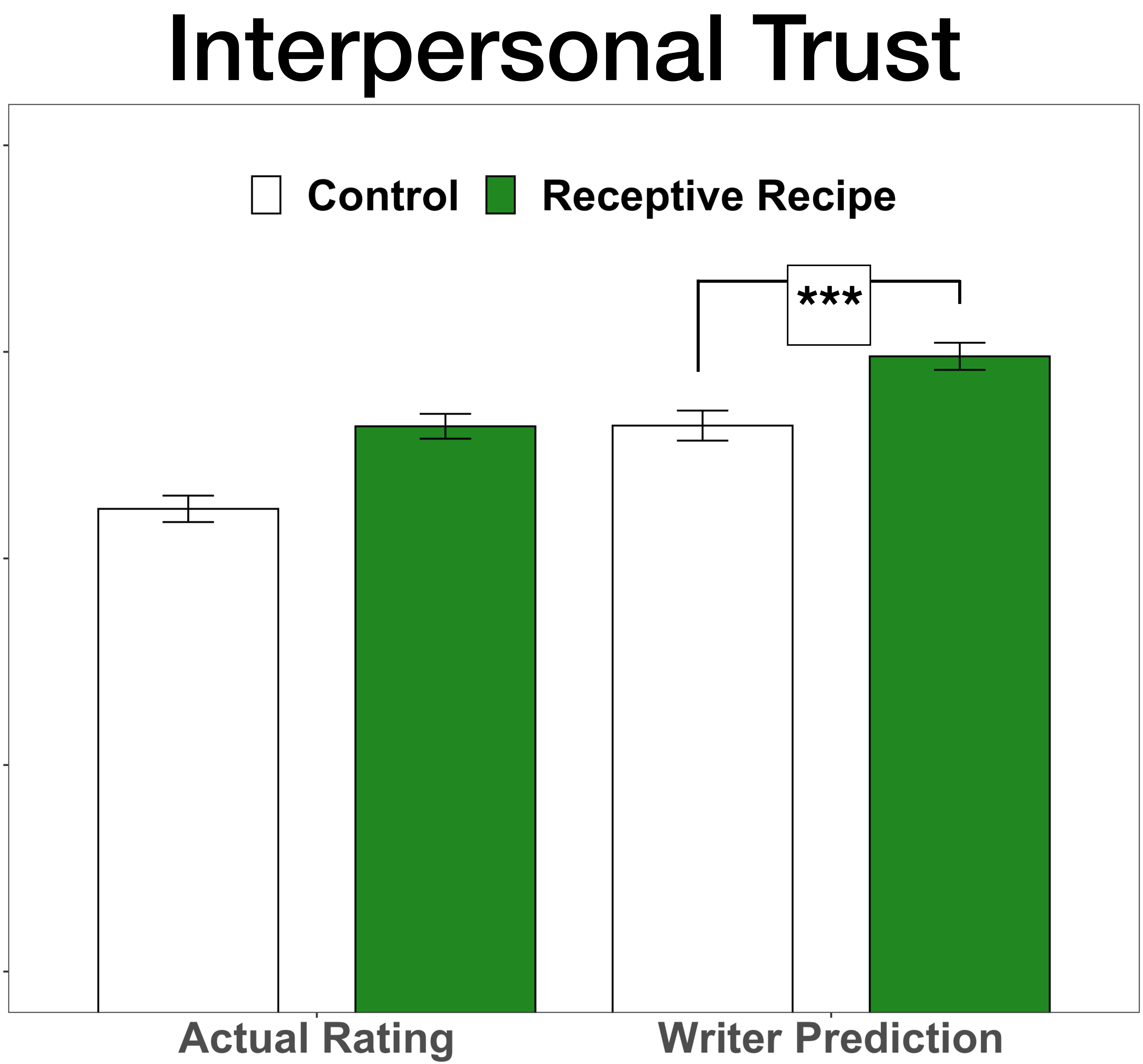
N = 771

The Receptiveness Recipe





Interpersonal Trust
6
5
4
3
2
Control
Receptive Recipe
***
Actual Rating


Interpersonal Trust
6
5
4
3
2
Control
Receptive Recipe
***
Actual Rating
Writer Prediction

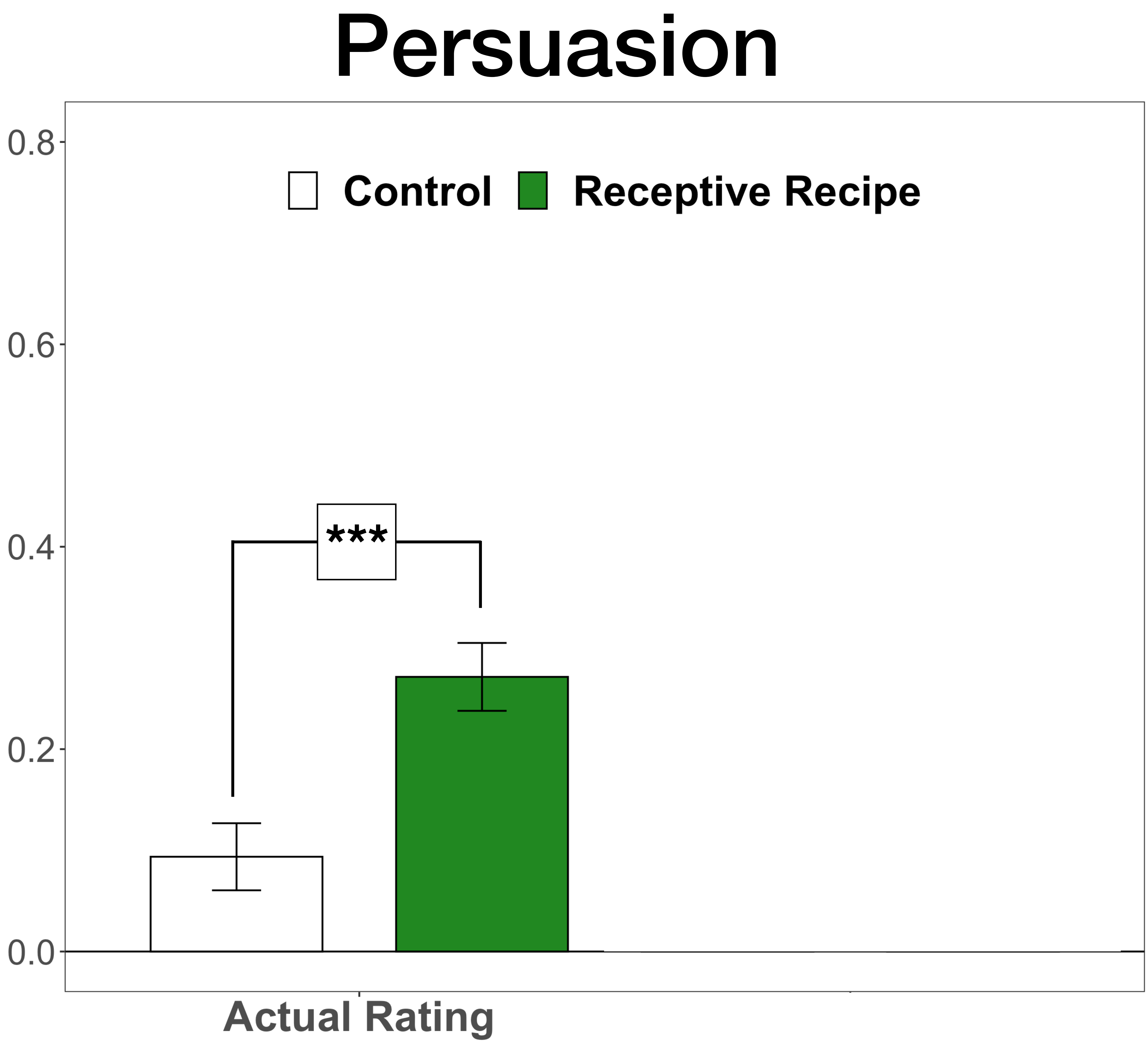
Persuasion

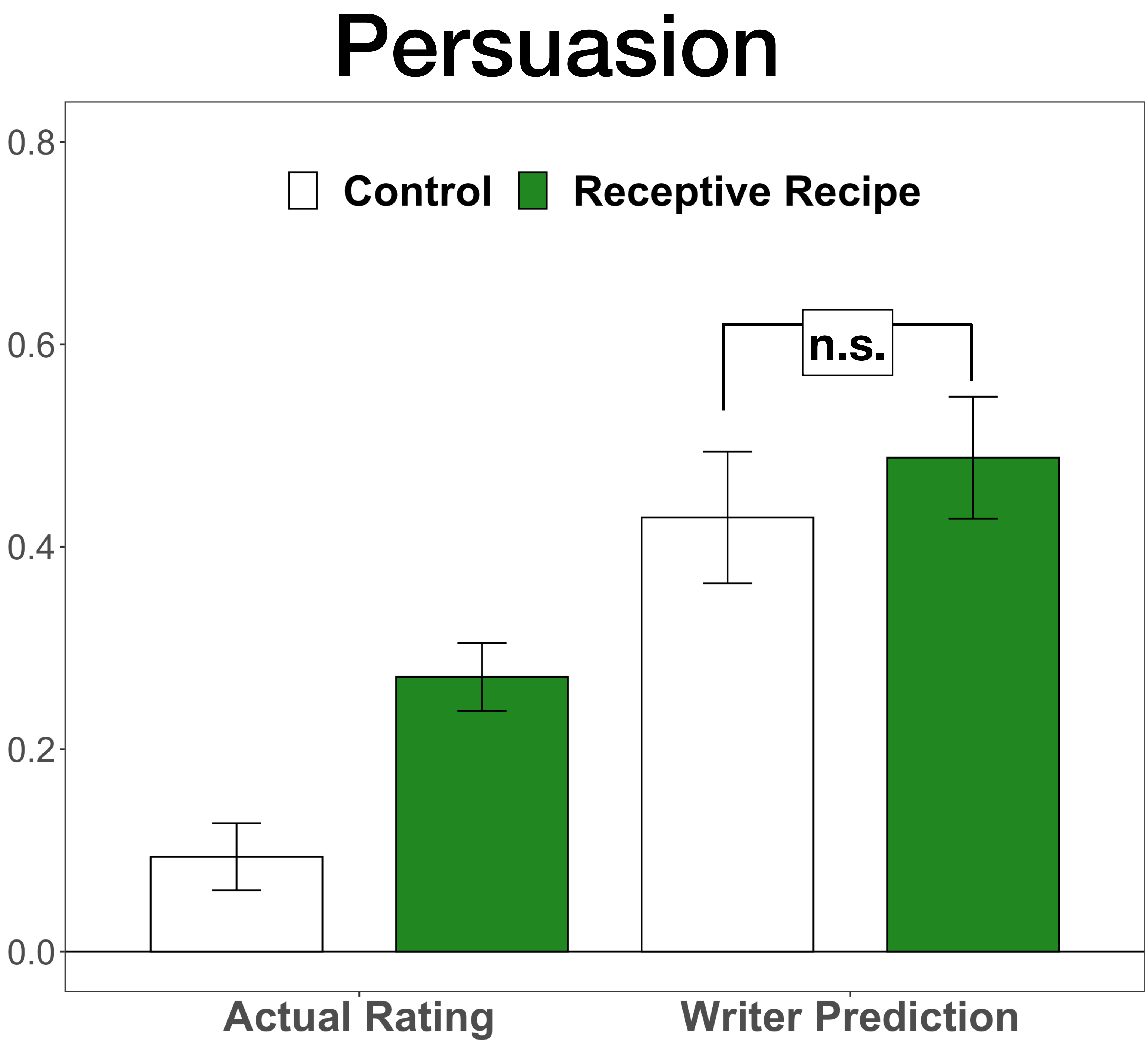
Persuasion

The person who wrote the response you read was selected because they generally disagree with your position (and with the person who wrote the original statement). We want to know whether their response was persuasive - that is, whether it affected your position on the issue.

How did your position change after reading their response?

-3	**0**	**+3**
My position is now further from their position	**My position has not changed**	**My position is now closer to their position**

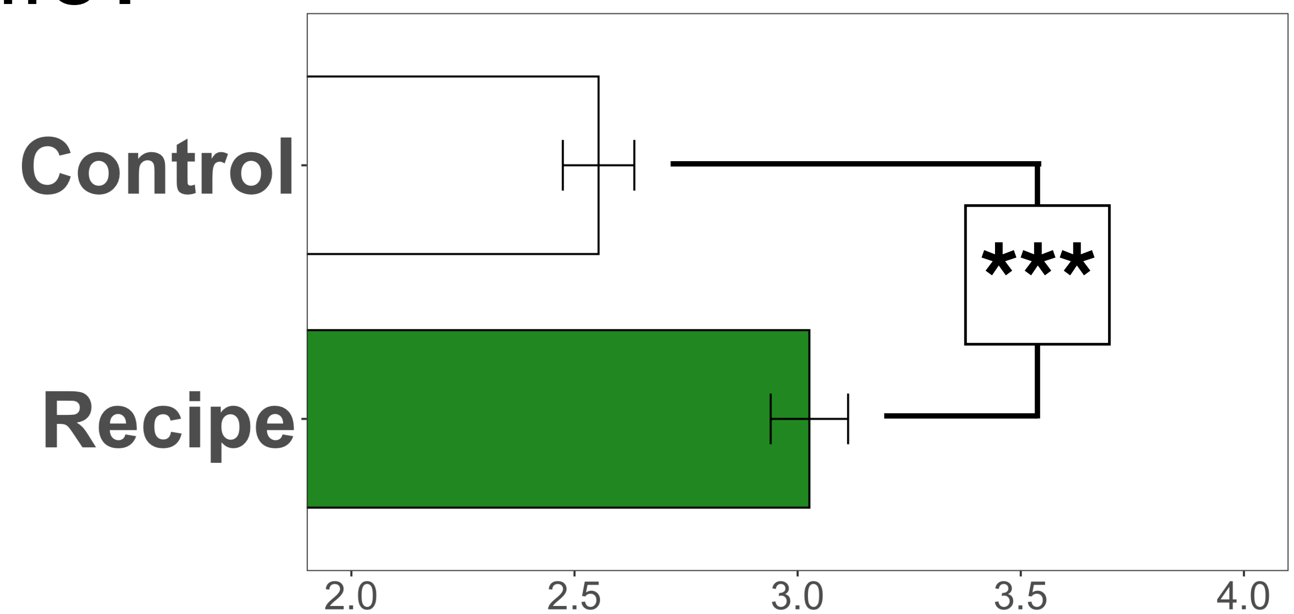

Persuasion
Control
Receptive Recipe
0.8
0.6
0.4
0.2
0.0
***
Actual Rating


Persuasion
Control
Receptive Recipe
n.s.
0.8
0.6
0.4
0.2
0.0
Actual Rating
Writer Prediction

Using the Recipe

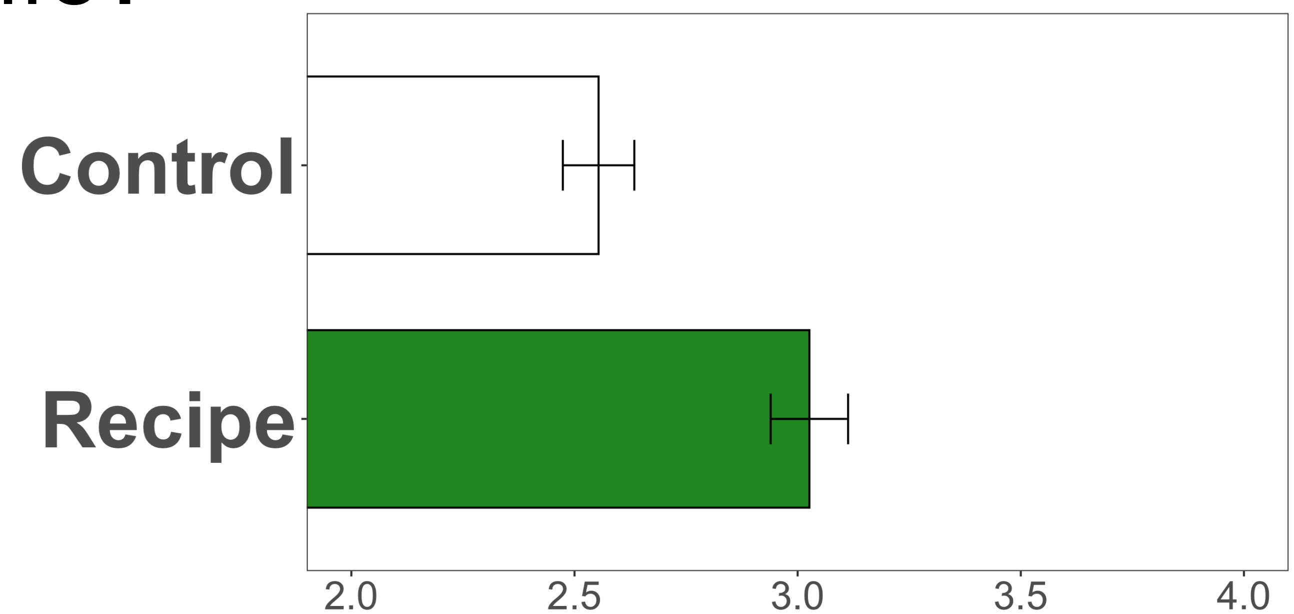
Using the Recipe

How **hard** would it be for you to adopt a similar style in future interactions with the disagreeing others in your life?

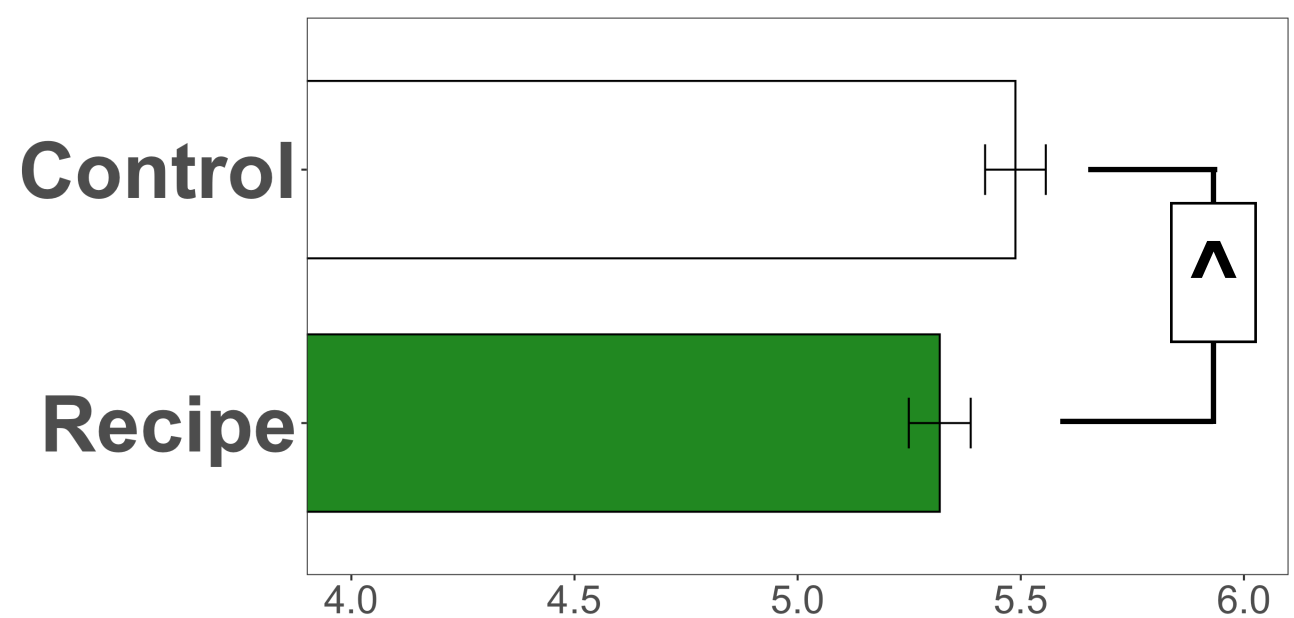


Using the Recipe

How **hard** would it be for you to adopt a similar style in future interactions with the disagreeing others in your life?



The next time you interact with disagreeing others in your life, how **likely** are you to adopt a similar style?



Conversational Receptiveness

...is measurable from behavioral data

...improves the health of conversations

...is misunderstood by people in conflict

Conversational Receptiveness

...is measurable from behavioral data

Study 1 - Mechanical Turk

...improves the health of conversations

...is misunderstood by people in conflict

Conversational Receptiveness

...is measurable from behavioral data ✓

Study 1 - Mechanical Turk

...improves the health of conversations ✓

Study 2 - HarvardX Online Courses

Study 3 - Wikipedia Editors

...is misunderstood by people in conflict

Conversational Receptiveness

...is measurable from behavioral data ✓

Study 1 - Mechanical Turk

...improves the health of conversations ✓

Study 2 - HarvardX Online Courses

Study 3 - Wikipedia Editors

...is misunderstood by people in conflict ✓

Study 4 - Local Government Officials

Study 5 - The Receptiveness Recipe

Conversational Receptiveness

...is measurable from behavioral data

Study 1 - Mechanical Turk

...improves the health of conversations

Study 2 - HarvardX Online Courses

Study 3 - Wikipedia Editors

...is misunderstood by people in conflict

Study 4 - Local Government Officials

Study 5 - The Receptiveness Recipe

```
>install.packages("politeness")
```