



A social-event based approach to sentiment analysis of identities and behaviors in text

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The core research questions

How do “people” feel
about different identities?

Can we learn this
from text?

Data comes from the “Arab Spring”

■ Algeria
■ Bahrain
■ Egypt
■ Iran
■ Islamic Republic of Iraq
■ Jordan
■ Kuwait
■ Lebanon
■ Libyan Arab Jamahiriya
■ Morocco
■ Oman
■ Qatar
■ Saudi Arabia
■ Syria
■ Tunisia
■ United Arab Emirates
■ Western Sahara
■ Yemen



- Newspaper data (700K articles)
 - LexisNexis, centered on 16 MENA countries
 - Major news outlets
 - 7/10 – 12/12

We use social events to infer affect

The
New York
Times

Last week, Egyptian officials accused
demonstrators

Traditionally:

“good” demonstrators

“bad” demonstrators

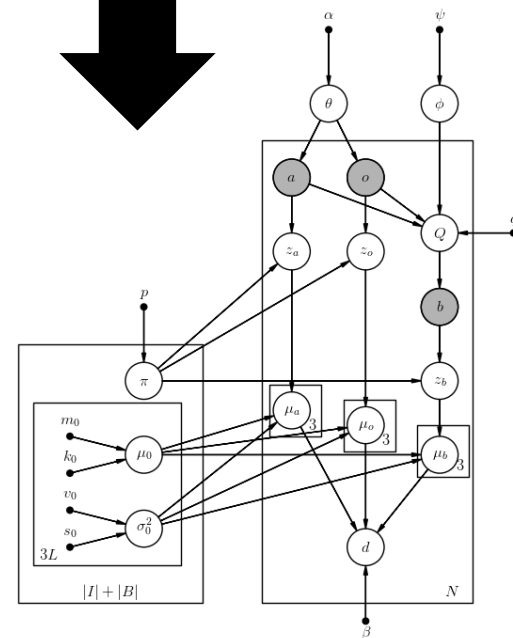
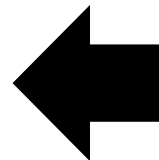
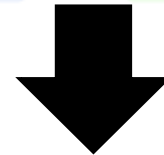

The present work:

Egyptian official
Identity

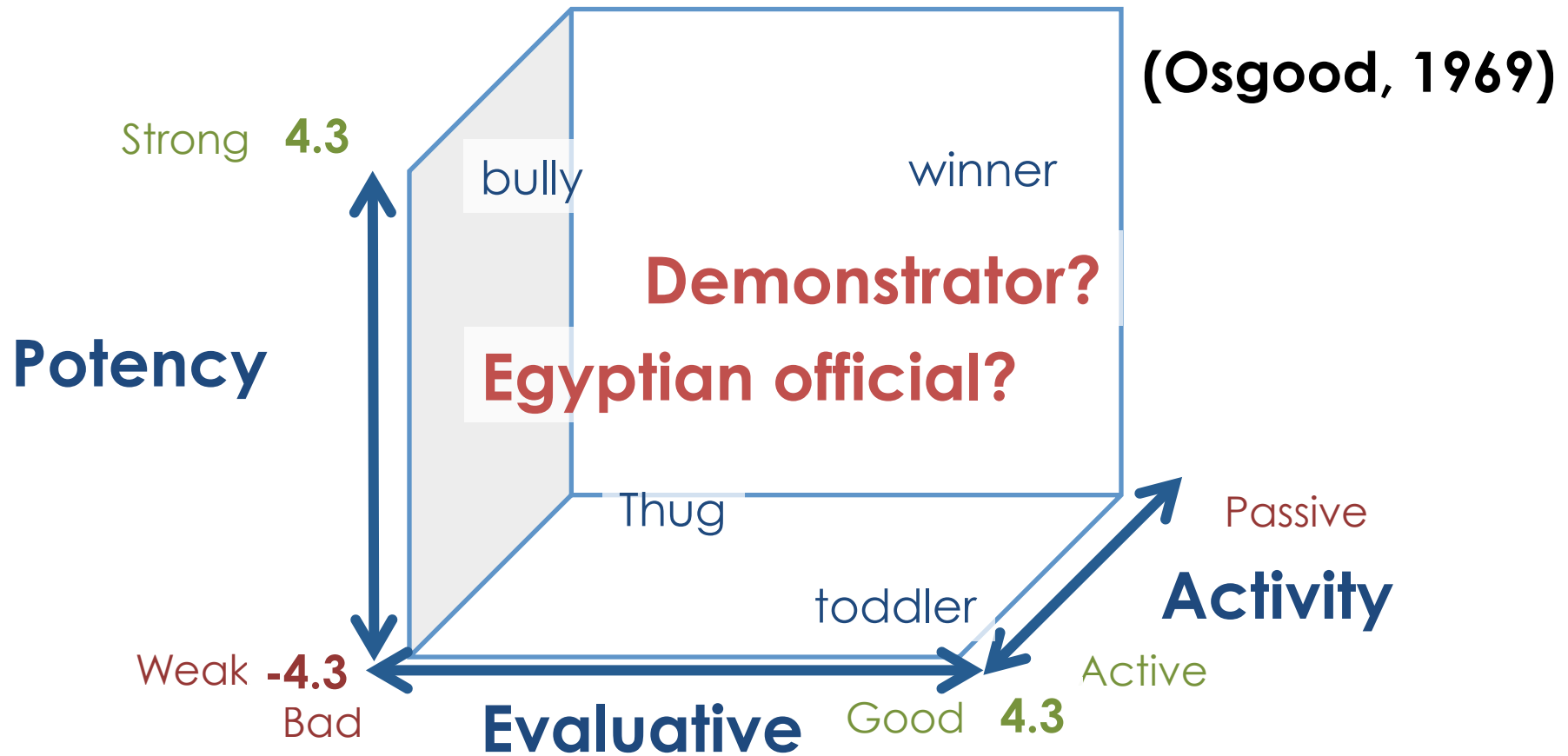
accuse
behavior

demonstrators
Other Identity

The
New York
Times



Affect Control Theory and sentiment space



- ACT scholars obtain this data via survey
- Assumed to be culturally-shared

Social events provide info on sentiment

 ? officials

 criticize

 women

Affect Control Theory (ACT) gives a mathematical model for this

ACT defines a mathematical model of this

officials

criticize

women

$$f = (A_e \quad A_p \quad A_a)$$

Unknown

$$(B_e \quad B_p \quad B_a)$$

Known

$$(O_e \quad O_p \quad O_a)$$

Known

Minimize $Deflection = \sum_i^9 (f_i - M_{i*}^T G(f))^2$



$$(A_e \quad A_p \quad A_a)$$

Known

Inference is harder with incomplete info

? officials

— accused

?

? demonstrators

We can use many events to appease this

~~?~~

officials

~~?~~

officials

—

criticize

—

accused

+

women

+

demonstrators

Meaning can/should diffuse through
multiple events

Caveat – multiple meanings for identities

Sometimes,

officials \neq officials

Solution:

Assume multiple latent “senses” of each identity/behavior

More on extracting social events, identities

1. Ran dependency parser, extracted all N -> V -> N
 2. Cleaned text using, e.g., stemming (accused -> accuse)
 3. Hand-curated list of identities and behaviors
- 102 identities, 87 behaviors, 10K events
 - Only 44% of identities in ACT dicts

A Bayesian Network to extract sentiment

Officials criticize demonstrators

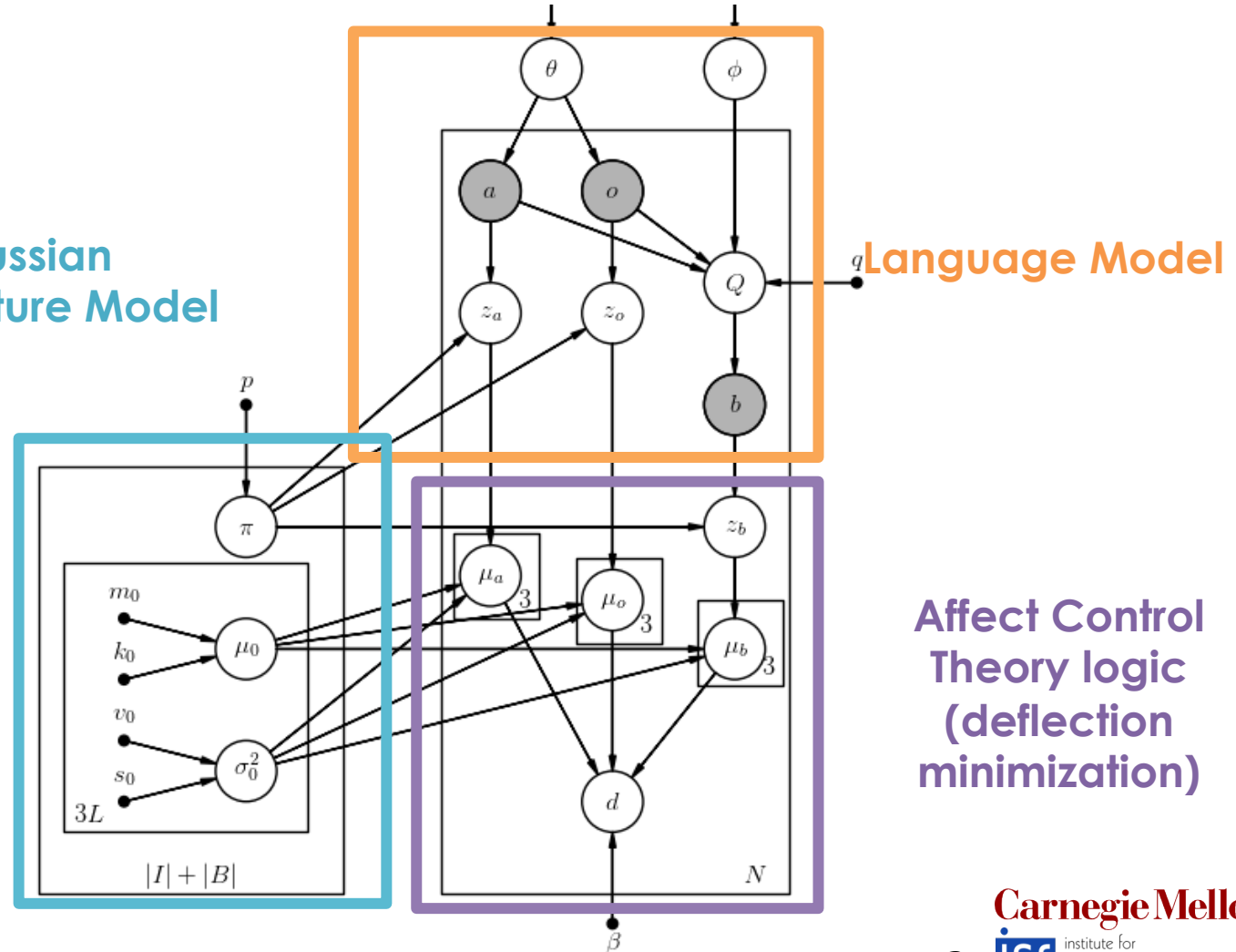
Gaussian
Mixture Model

ACT Dictionary

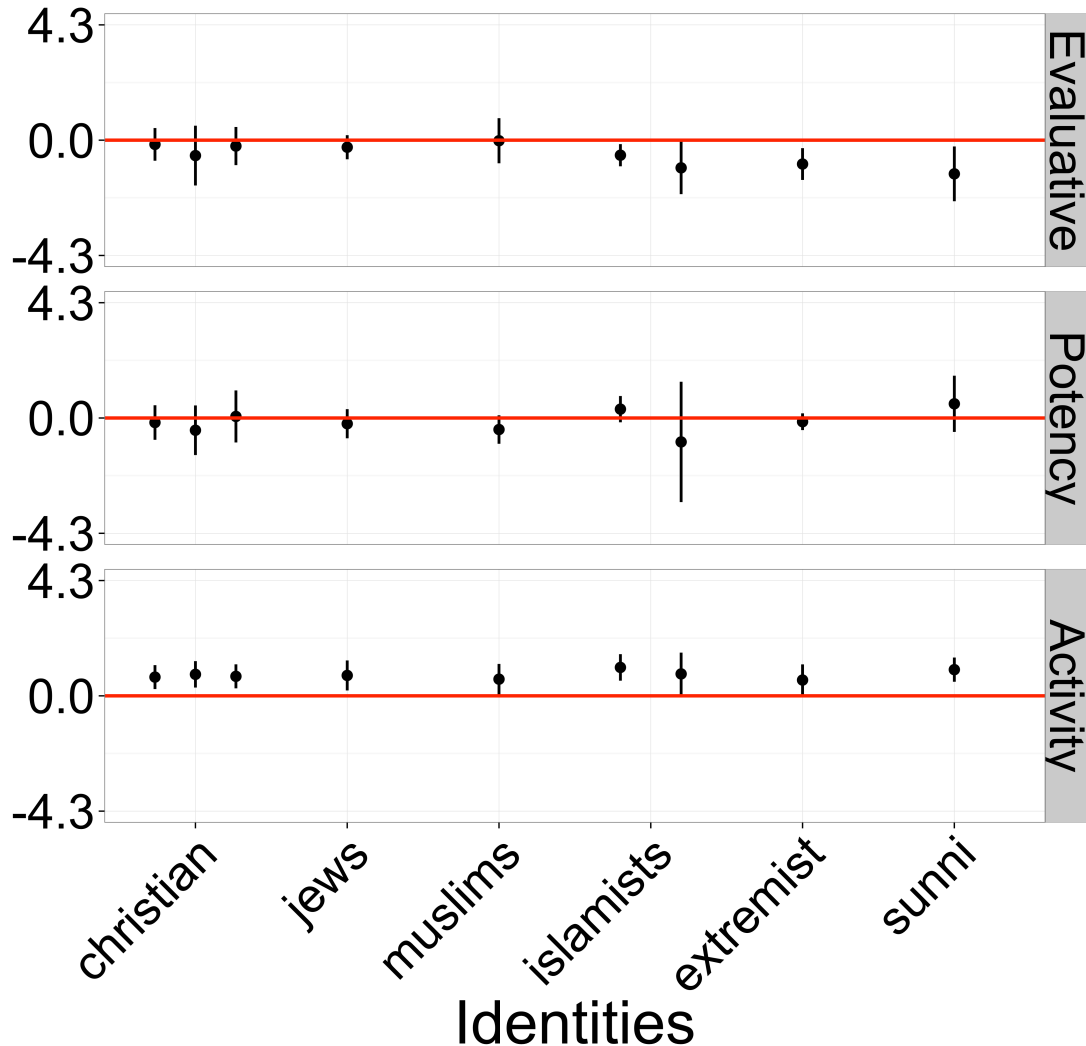
criticize [-4 3 2]

women [4 1 4]

....



Results for a subset of (religious) identities



Concluding

- Current work
 - New approach to sentiment mining for identities
 - Several parts of the process need work
- Future/Thesis work
 - Extract identities/behaviors from text automatically
 - Intermingling cognitive frameworks and Affect Control Theory

Thanks!!

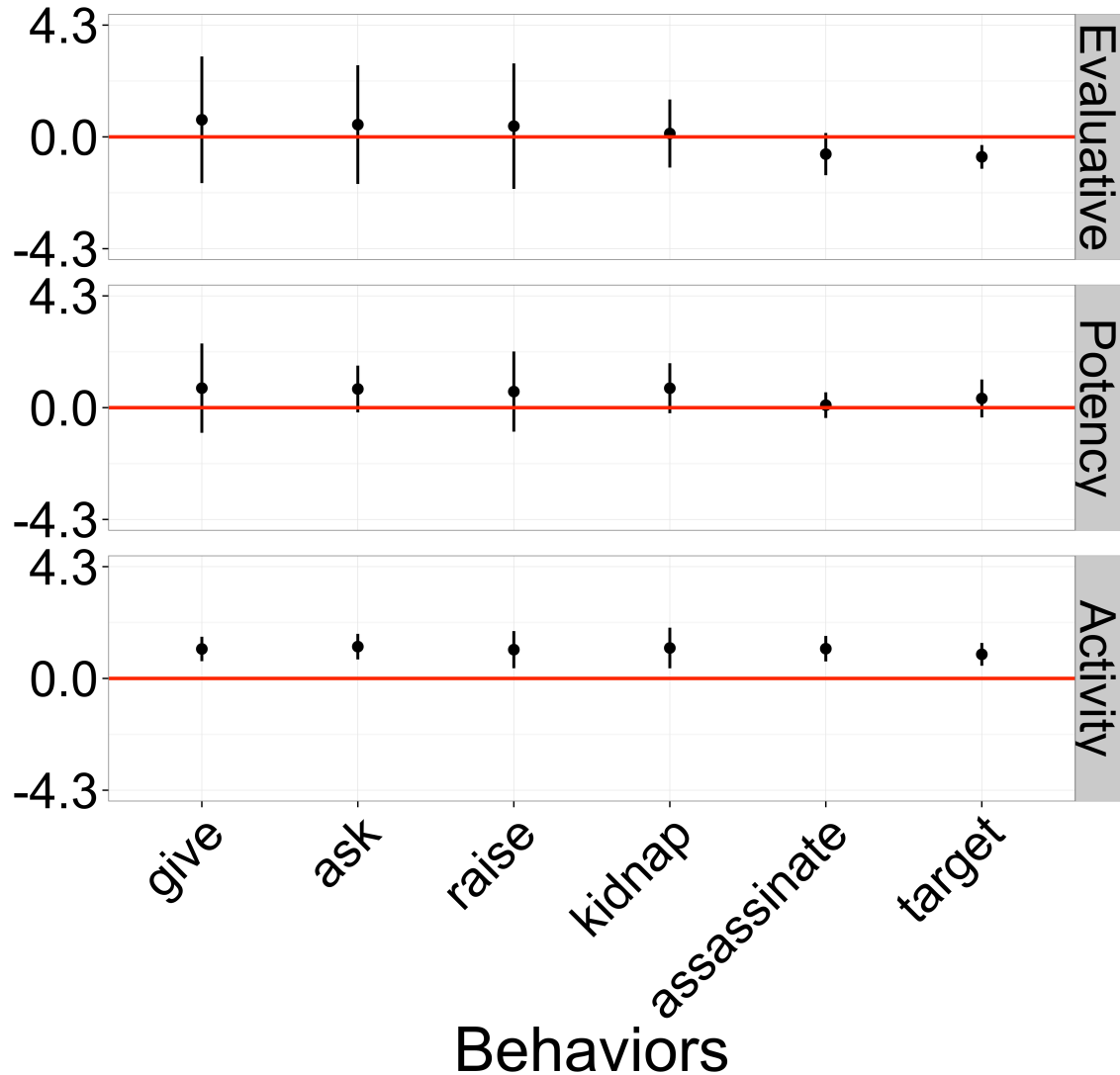
- In submission
- Replication data+code
github.com/kennyjoseph/act_paper_public
- Me:
Kenny Joseph
[@_kenny_joseph](https://cs.cmu.edu/~kjoseph)
Looking for jobs...

Extra Slides

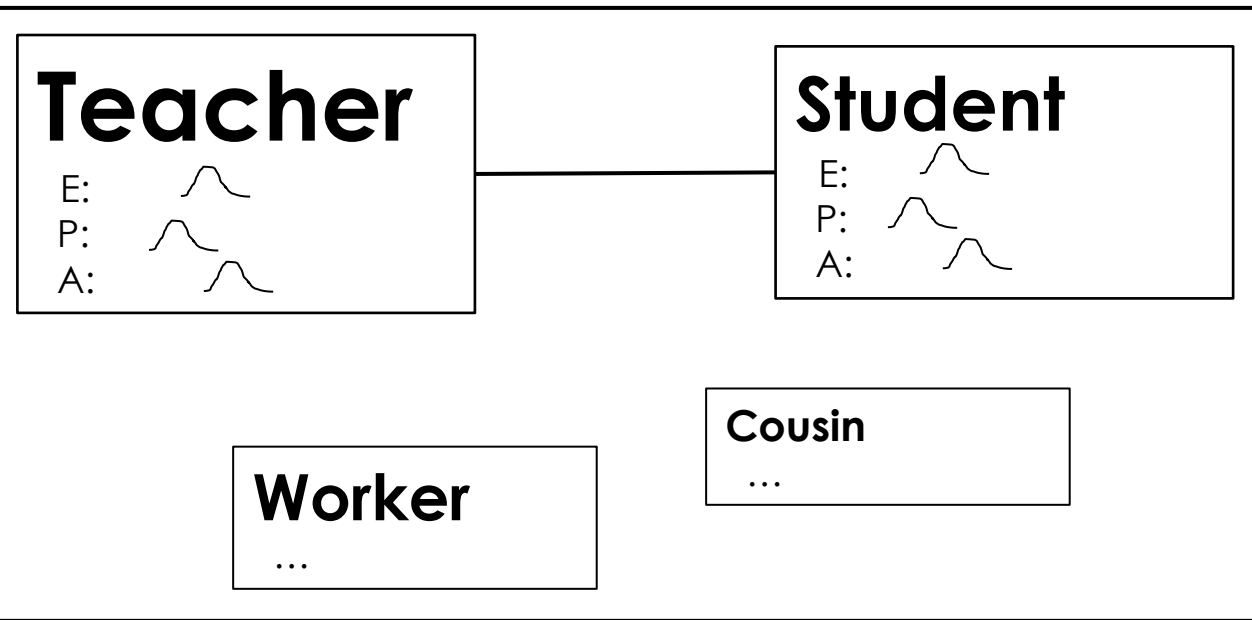
More details on the model

- Inference performed using Monte-Carlo EM
- Difficult parts of the inference
 - Inferring which latent topic/“sense” for a given event
 - Efficient usage of deflection principle
- Tested model using held-out events compared to various baselines

Results for behaviors



Can choose identities in context



$f(\text{Activation, Relationships, EPA})$



student
 worker?
 classmate?
 traveler?
 cousin?

Teacher

advises

2.45 1.75 0.29

2.12 1.59 0.98

1.49 0.31 0.75

More details on the model

1. Draw an actor and an object; $a \sim \text{Cat}(\theta)$ $o \sim \text{Cat}(\theta)$
2. Draw a behavior; $b \sim \text{Cat}(Q)$
3. Draw a latent sense for a , b and o ; $z_a \sim \text{Cat}(\pi_a)$ $z_b \sim \text{Cat}(\pi_b)$ $z_o \sim \text{Cat}(\pi_o)$

4. Draw EPA profiles for a , b , and o

- $\mu_{a,e} \sim N(\mu_{0,z_a,e}; \sigma_{0,z_a,e}^2)$ $\mu_{a,p} \sim N(\mu_{0,z_a,p}; \sigma_{0,z_a,p}^2)$ $\mu_{a,a} \sim N(\mu_{0,z_a,a}; \sigma_{0,z_a,a}^2)$
- $\mu_{b,e} \sim N(\mu_{0,z_b,e}; \sigma_{0,z_b,e}^2)$ $\mu_{b,p} \sim N(\mu_{0,z_b,p}; \sigma_{0,z_b,p}^2)$ $\mu_{b,a} \sim N(\mu_{0,z_b,a}; \sigma_{0,z_b,a}^2)$
- $\mu_{o,e} \sim N(\mu_{0,z_o,e}; \sigma_{0,z_o,e}^2)$ $\mu_{o,p} \sim N(\mu_{0,z_o,p}; \sigma_{0,z_o,p}^2)$ $\mu_{o,a} \sim N(\mu_{0,z_o,a}; \sigma_{0,z_o,a}^2)$

5. Draw a deflection score for the event

- $d \sim \text{Laplace}(\sum_i^9 (f_i - M_{i*}^T G(f))^2, \beta)$ where $f = [\mu_{a,e}, \mu_{a,p}, \mu_{a,a}, \mu_{b,e}, \mu_{b,p}, \mu_{b,a}, \mu_{o,e}, \mu_{o,p}, \mu_{o,a}]$

ACT is a “first order social effects” model

Teacher beats up student

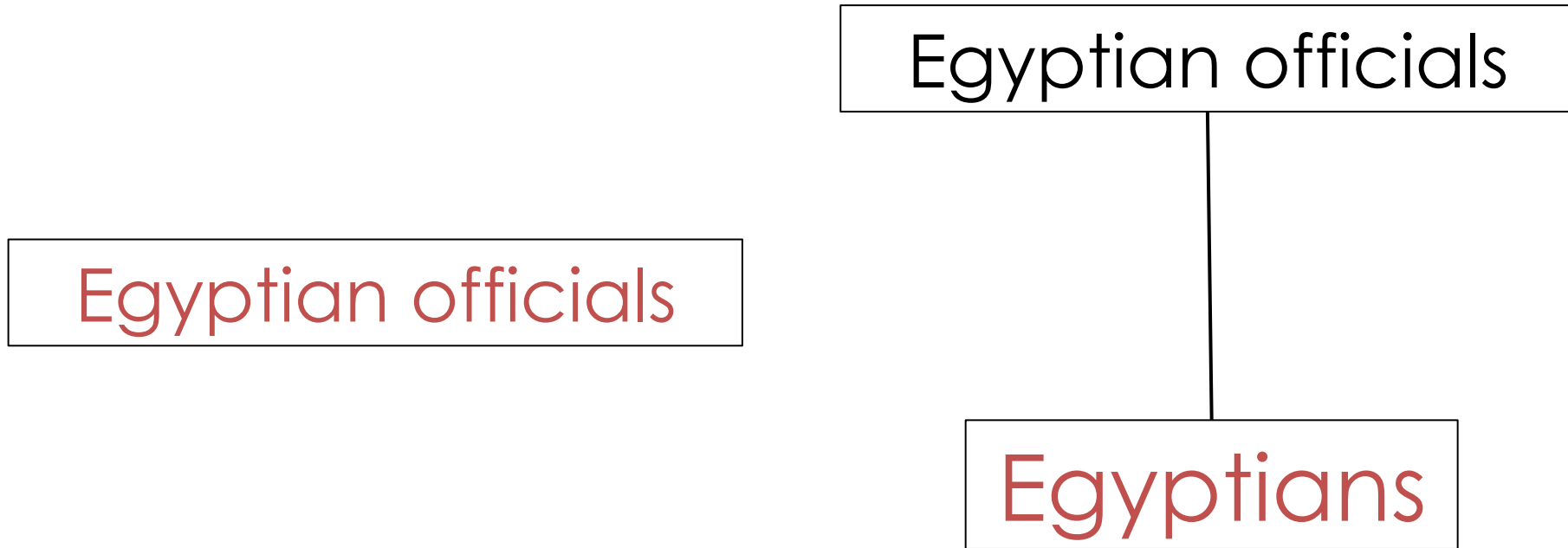
School official

child

What we learn should “filter” to encompassing concepts

Also makes sense that related concepts somehow “influence” perceptions

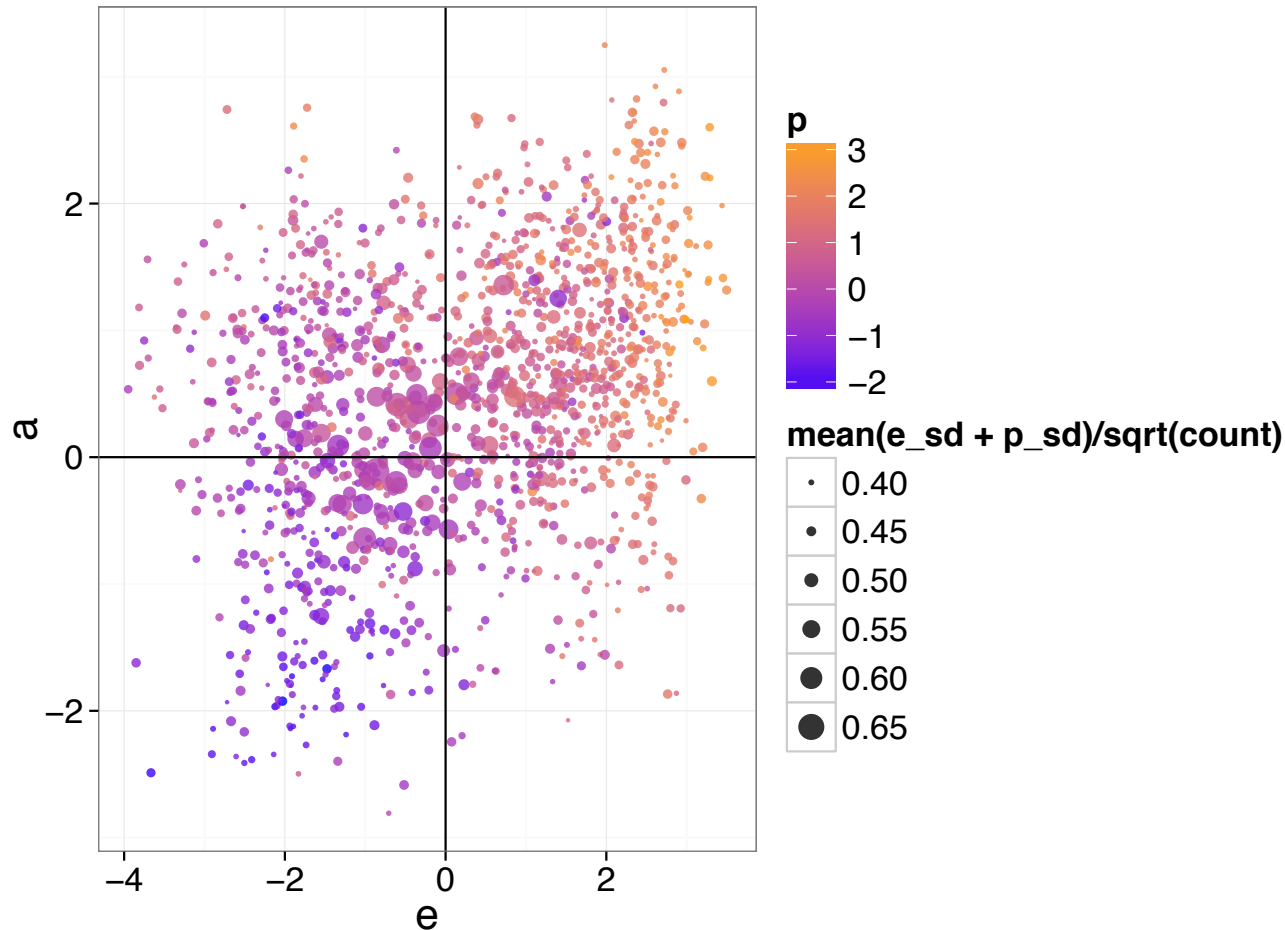
Future work: incorporate cognitive relations



Can also consider other relations
between identities

EPA Correlations in existing ACT dictionaries

- From the Indiana survey



ACT provides a mathematical model of how these meanings change and are maintained during social events

Teacher			advises			student		
2.45	1.75	0.29	2.12	1.59	0.98	1.49	0.31	0.75
Good/ Bad	Strong/ Weak	Active/ Passive						
$f = (A_e$	A_p	A_a	B_e	B_p	B_a	O_e	O_p	$O_a)$

$$Deflection = \sum_i^9 (f_i - M_{i*}^T G(f))^2 = .08$$

(This) Teacher			beats up			(this) student		
2.73	1.34	0.95	2.12	1.59	0.98	1.95	-0.58	0.51

Deflection = 15.4

(This) Teacher			(This) student		
-2.15	1.04	1.61	-2.23	0.65	-0.02

ACT defines what social events change

You see:

You think:

Then you see:

Teacher			beats up			student		
2.45	1.75	0.29	-1.92	1.00	1.62	1.49	0.31	0.75
Good/ Bad	Strong/ Weak	Active/ Passive						

Now you think: $M_{i*}^T G(f)$

(This) Teacher

-2.15 1.04 1.61

(This) student

-2.23 0.65 -0.02

ACT provides a mathematical model of how the meanings change and are maintained during *social events*

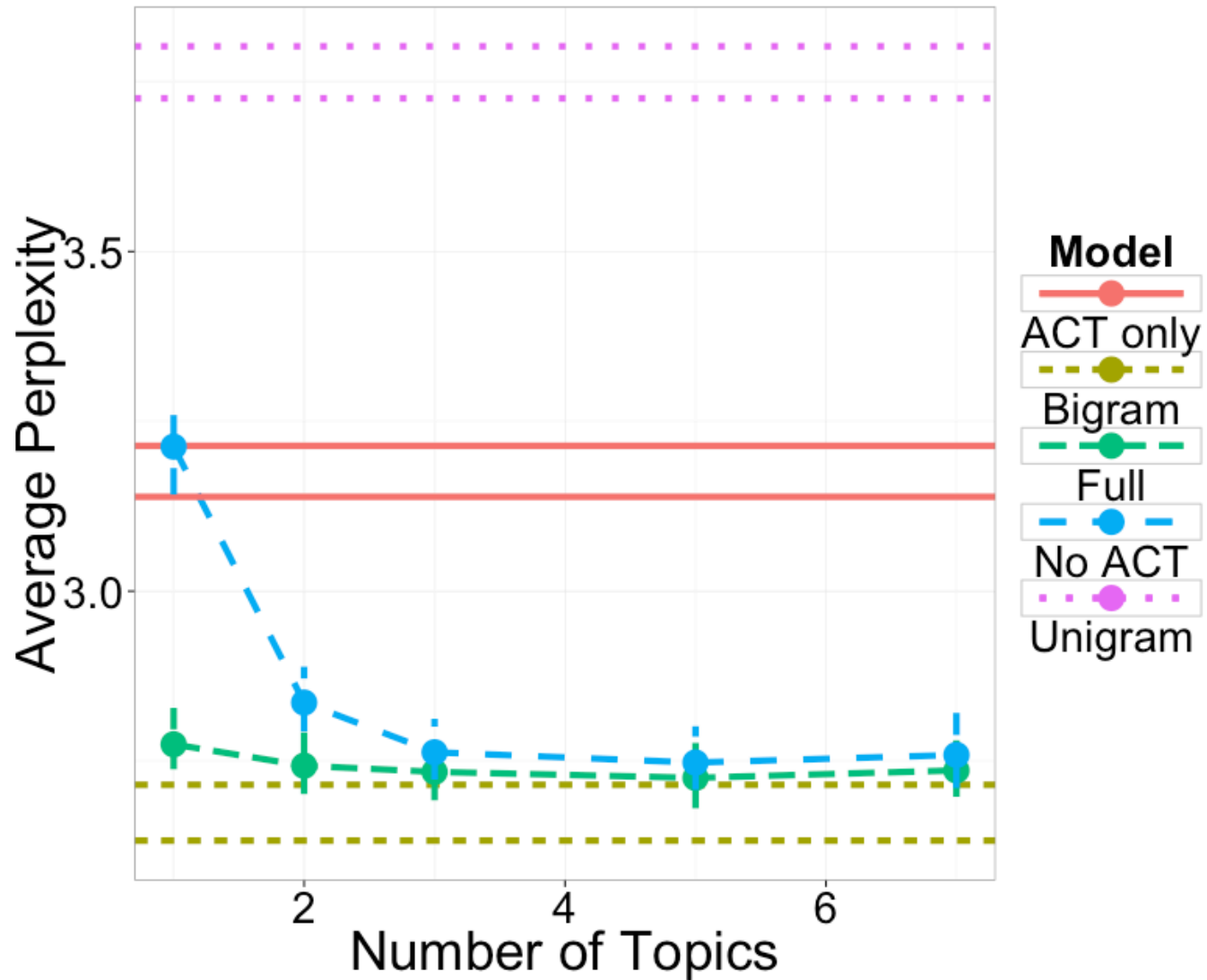
$$f = \left(\begin{array}{c|c|c} \text{Teacher} & \text{instructs} & \text{student} \\ \hline A_e & B_e & O_e \\ A_p & B_p & O_p \\ A_a & B_a & O_a \end{array} \right)$$

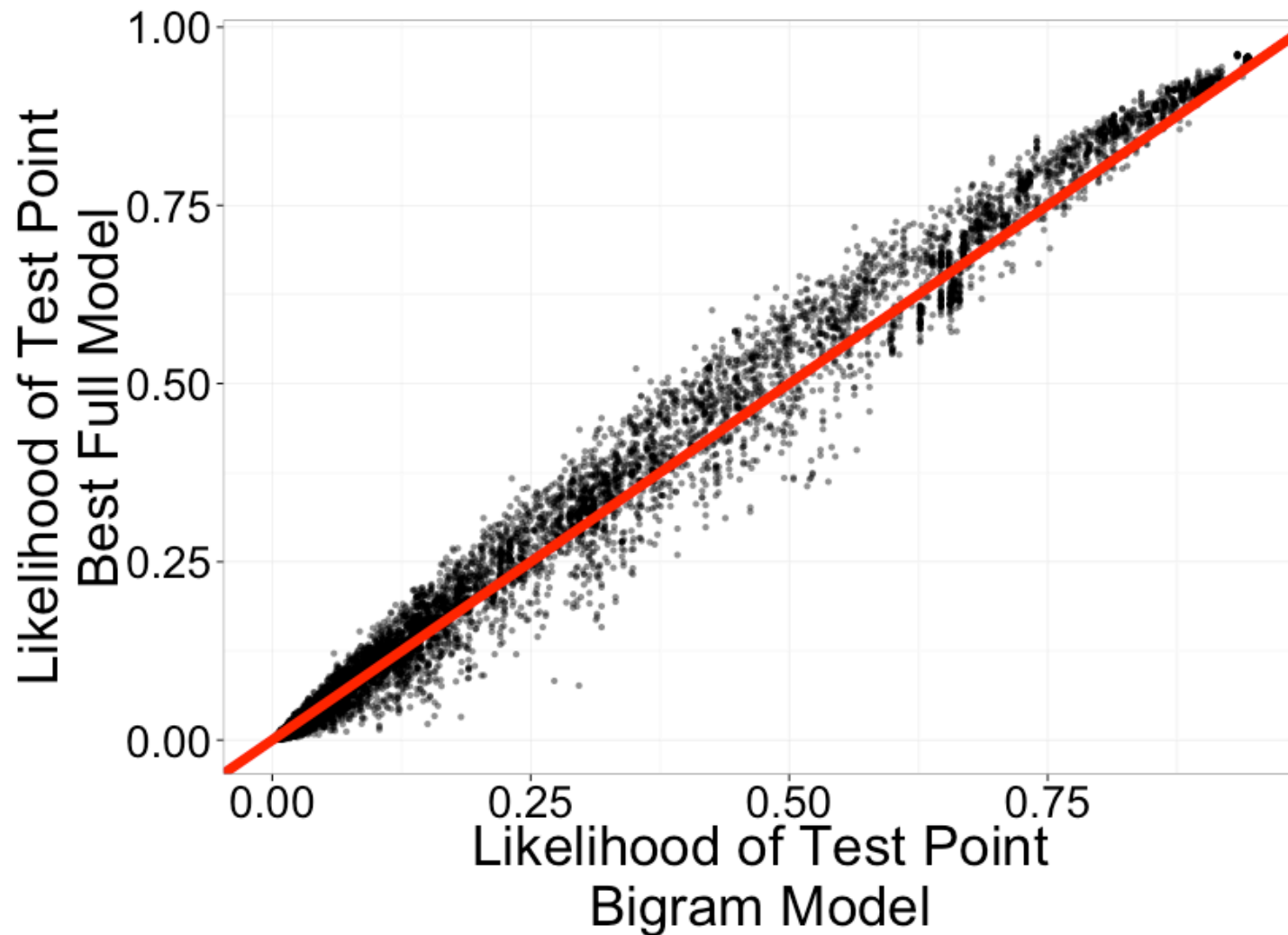
$$Deflection = \sum_i^9 (f_i - M_{i*}^T G(f))^2 \quad \text{Teacher instructs student (Deflection: 0.8)}$$

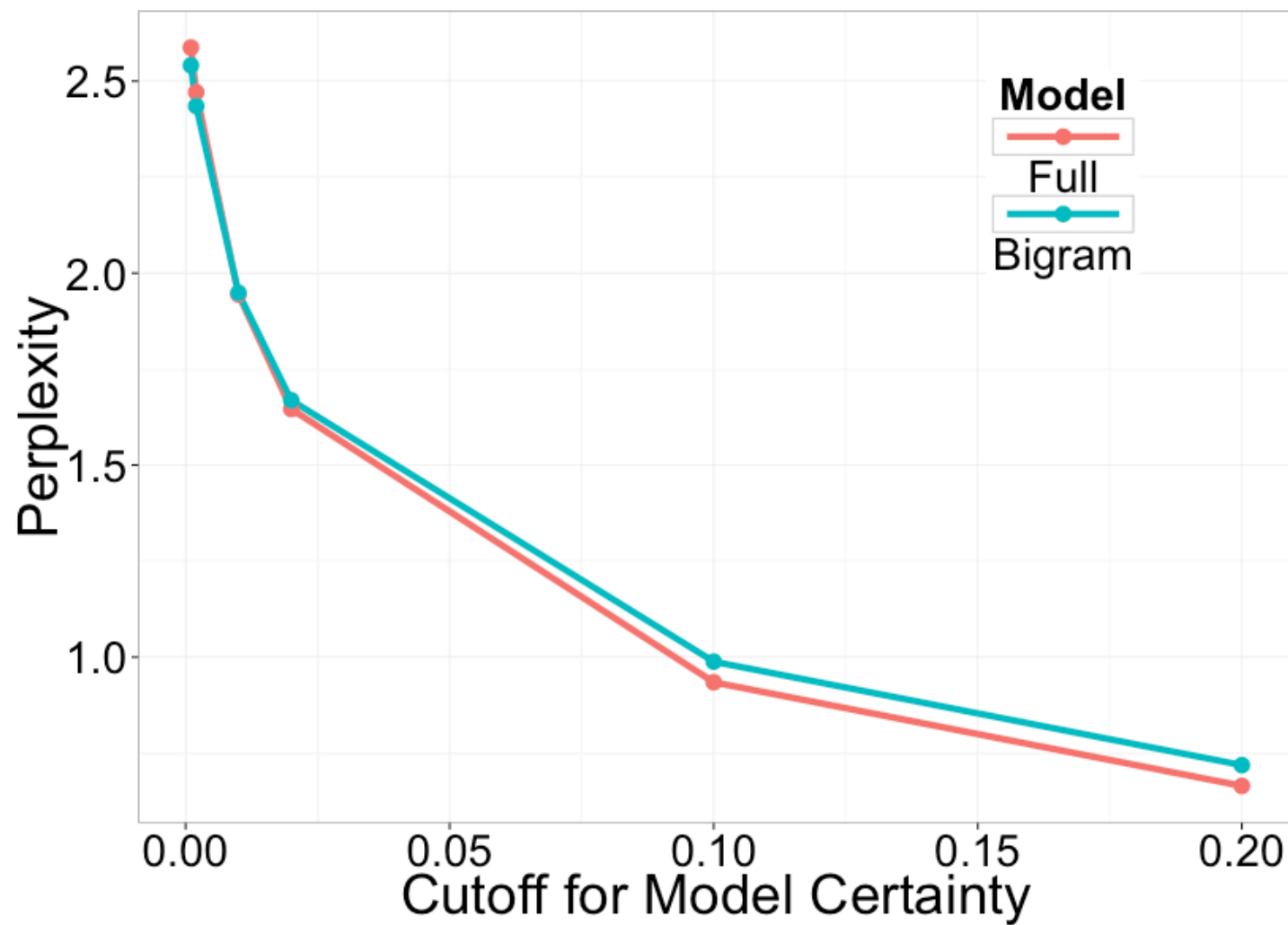
$$G(f) = \begin{bmatrix} 1 & A_e & A_p & A_a & B_e & B_p & B_a & O_e & O_p & O_a \\ B_e A_e & B_p A_e & O_e A_e & A_e O_p & A_p B_e & A_p B_p & & & & \\ A_p O_p & A_p O_a & A_a B_a & B_e O_e & B_e O_p & O_e B_p & B_p O_p & & & \\ B_p O_a & B_a O_p & B_e O_e A_e & B_p A_e O_p & A_p B_p O_p & A_p B_p O_a & & & & \end{bmatrix}$$

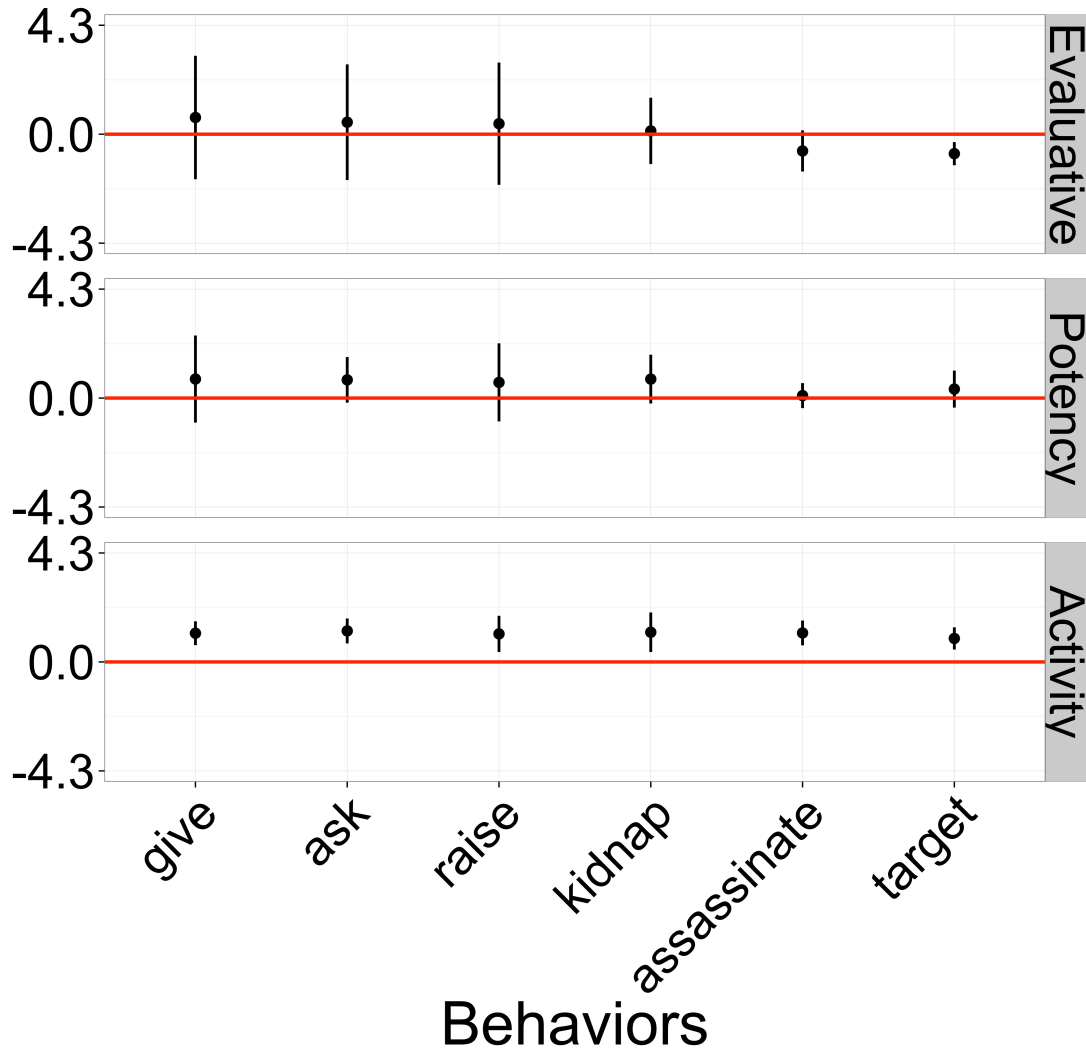
$$M = \begin{pmatrix} c_{1,1} & -.09 & \dots & c_{1,29} \\ .445 & c_{22} & \dots & c_{2,29} \\ \vdots & \vdots & \ddots & \vdots \\ .025 & 0 & \dots & c_{9,29} \end{pmatrix}$$

Predicts pretty well

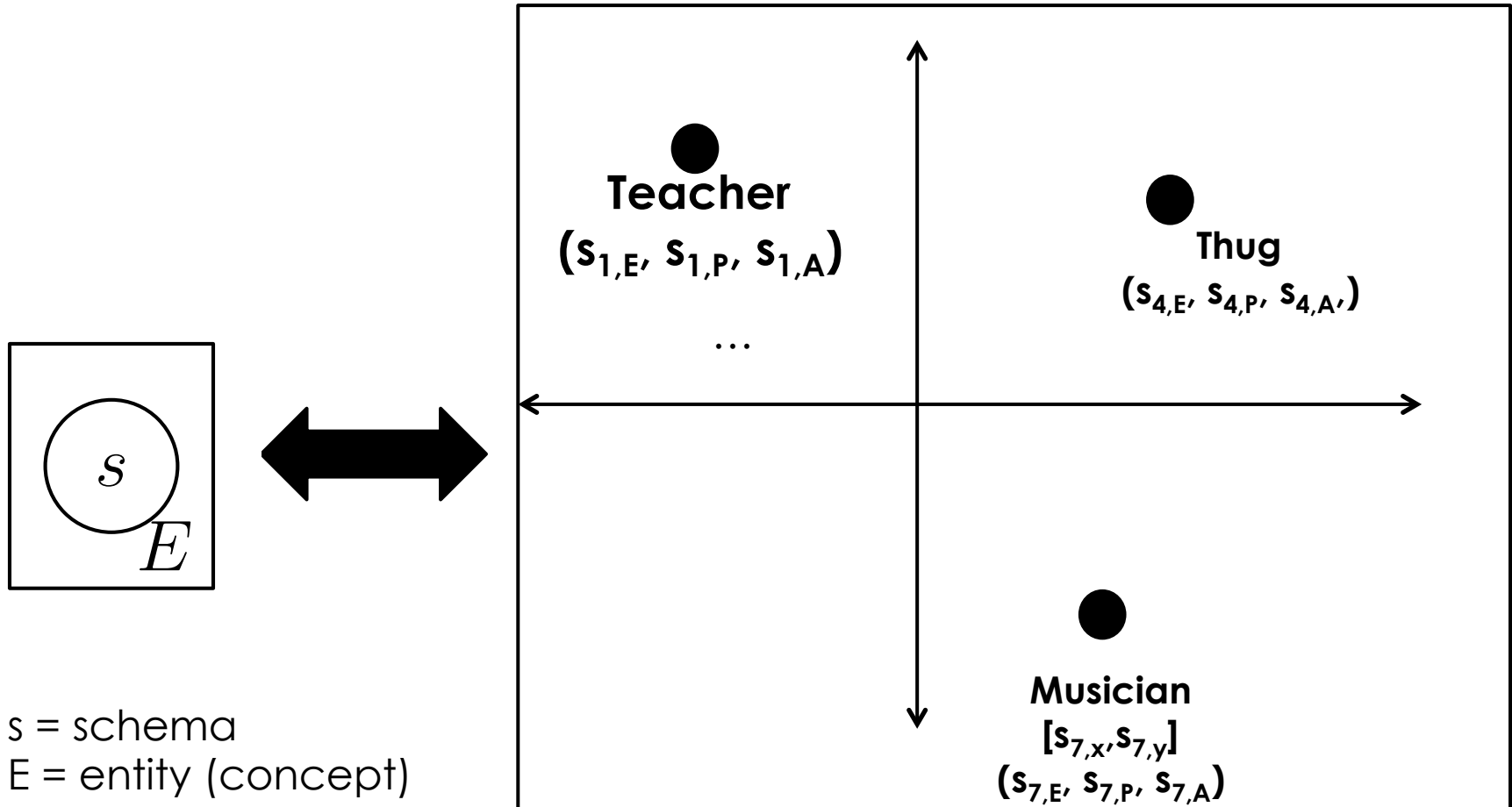








Probabilistic graphical model of LCSS



Each variable s is a 6-dim. representation of a schema