

# Tutorial



## Mental models as probabilistic programs



Tobias Gerstenberg

Kevin Smith

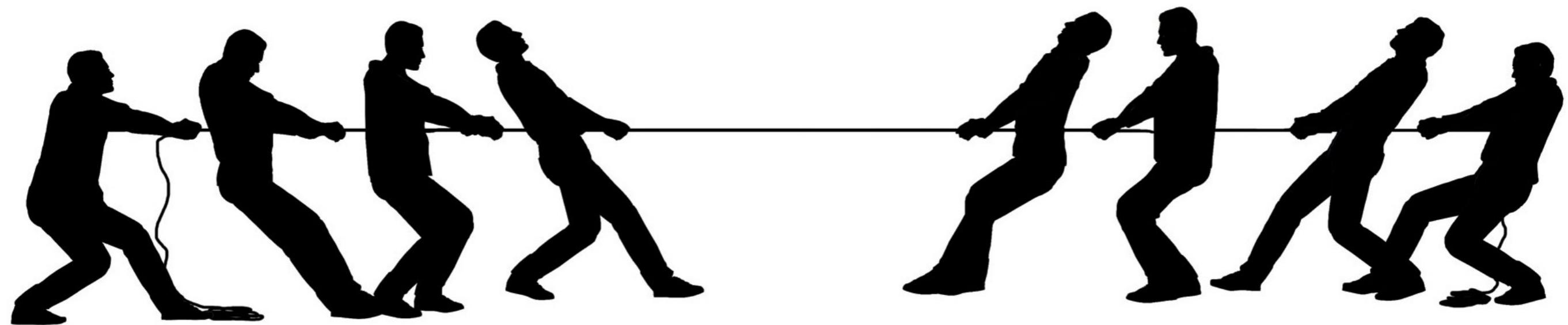
October 12th, 2017

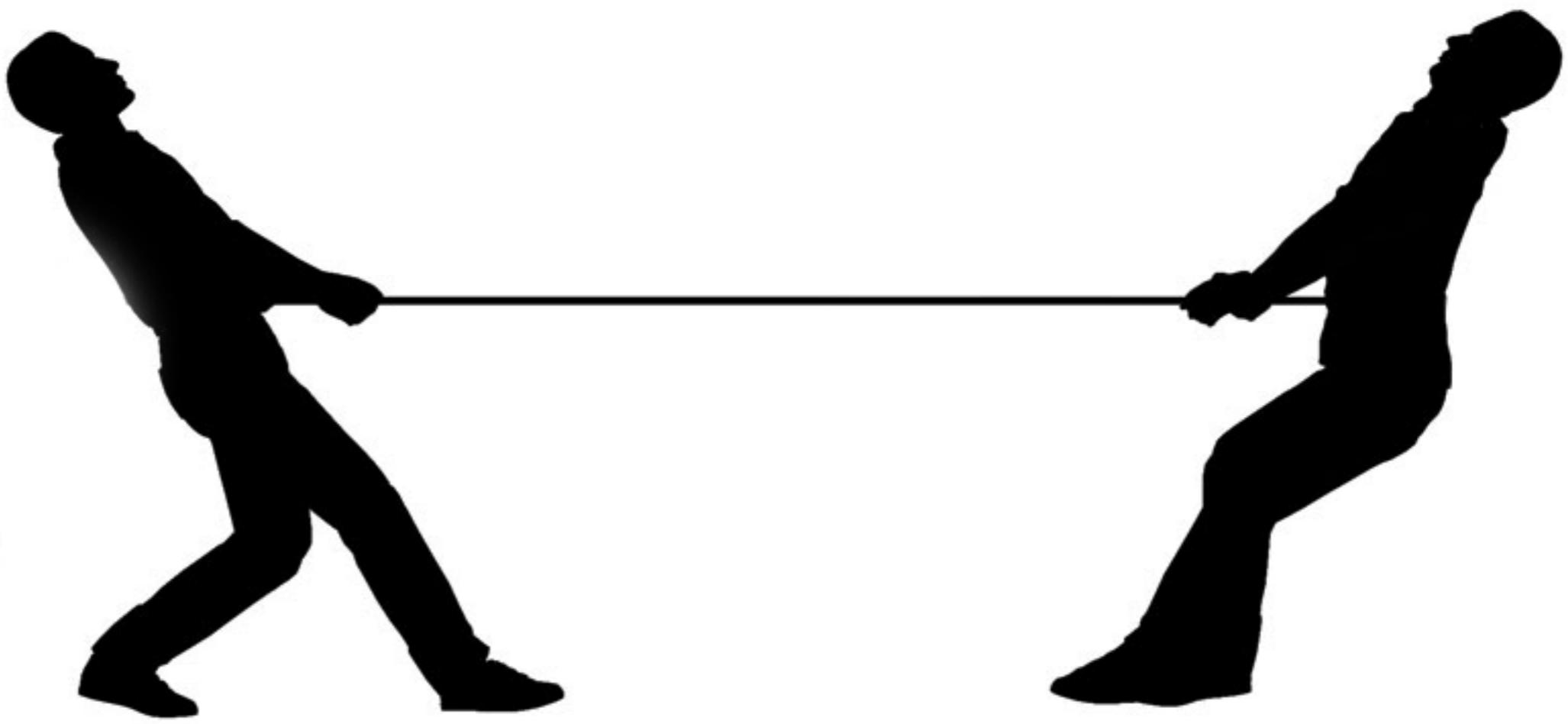


"Progress in science depends on new techniques, new discoveries and new ideas, probably in that order."

-Sydney Brenner

# Tug of War





Tom

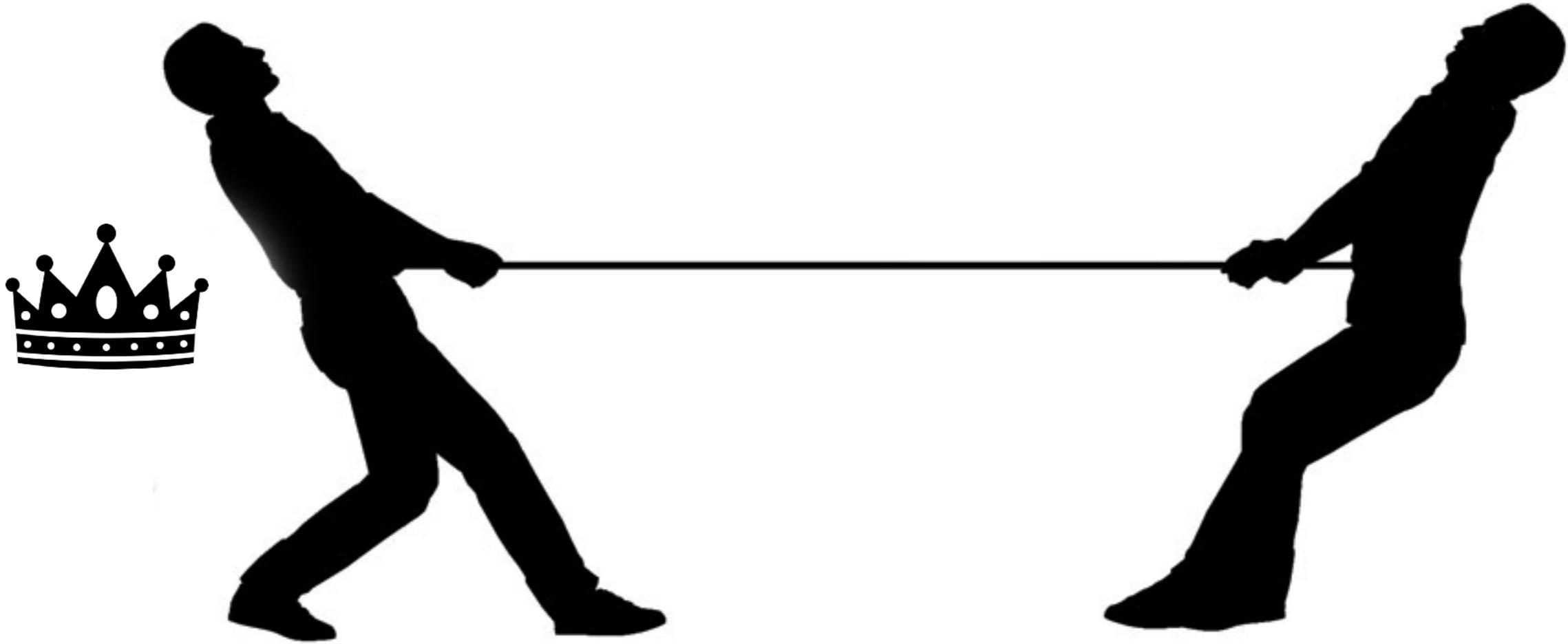
Steve



Tom

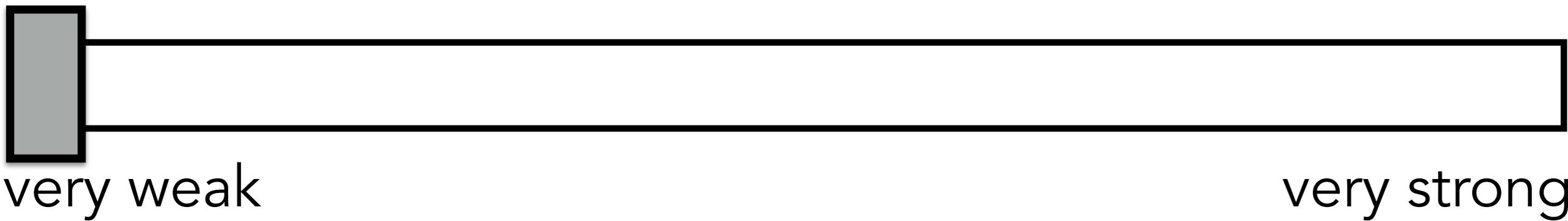


Steve



Tom

Steve



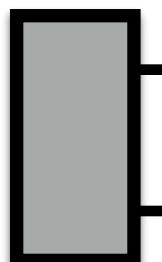


Bill



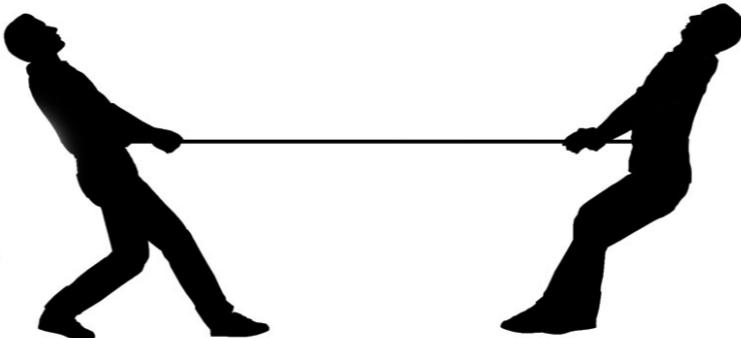
Mark

Nick



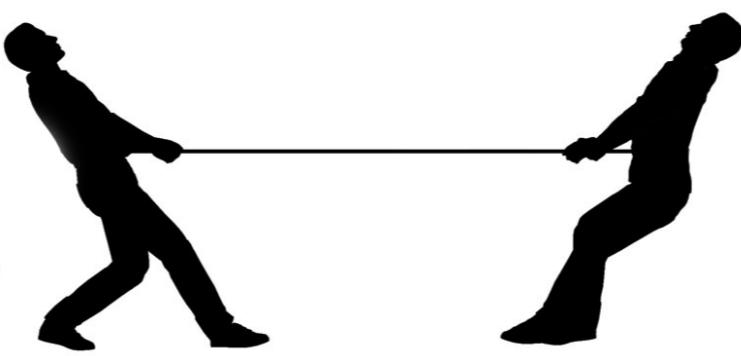
very weak

very strong



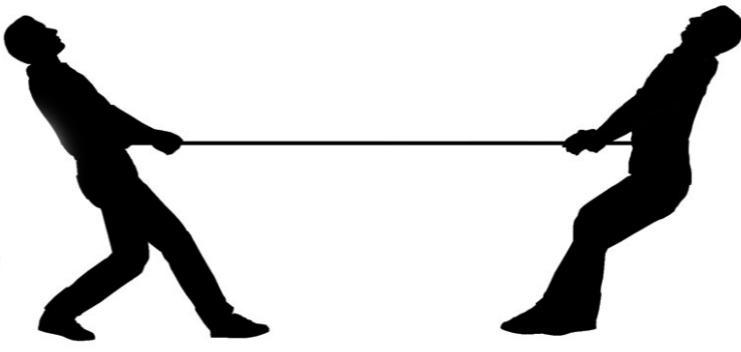
Tom

Steve



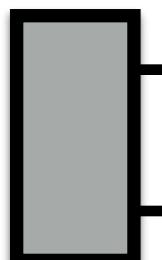
Bill

Steve



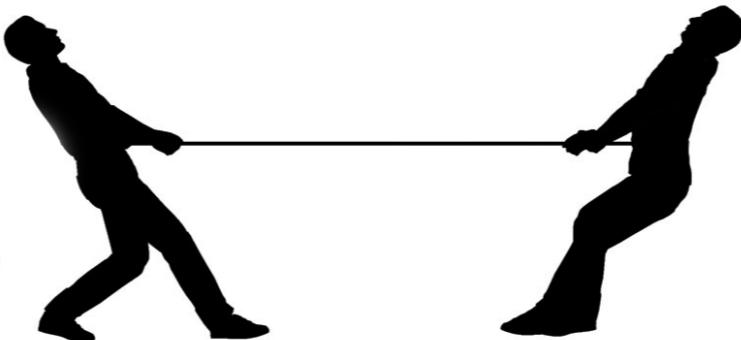
Ryan

Steve



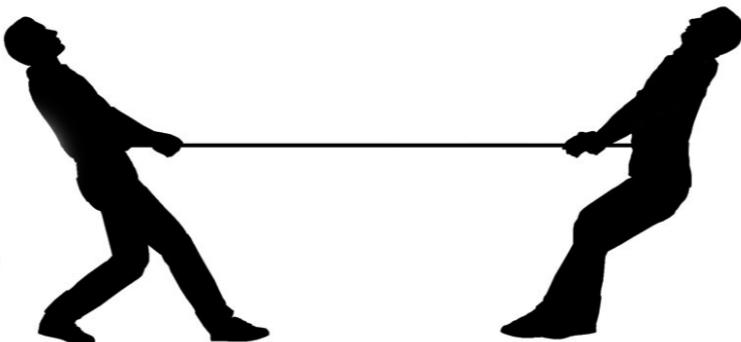
very weak

very strong



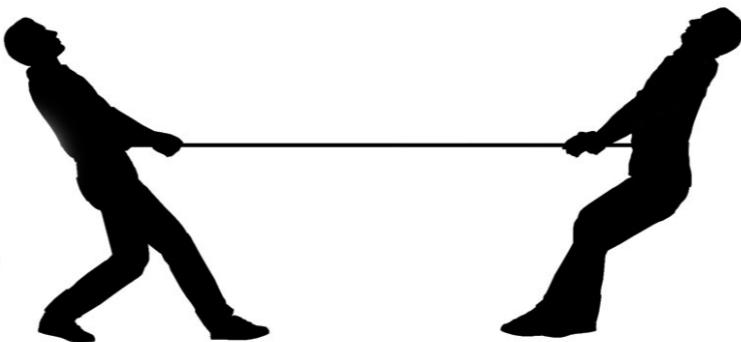
Tom

Steve



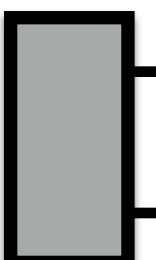
Bill

Steve



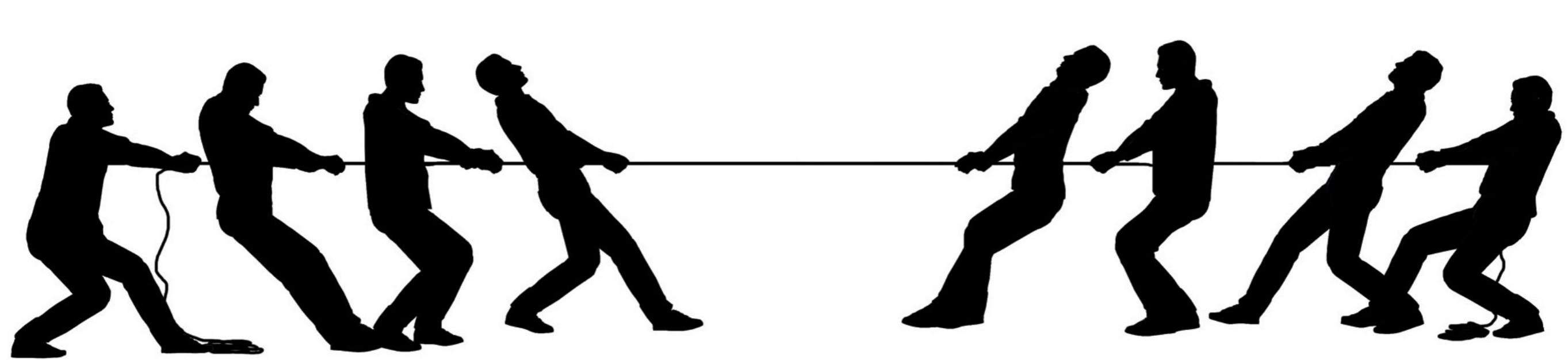
Ryan

Steve



very weak

very strong



## Concepts:

person

strength

teams

effort

winner

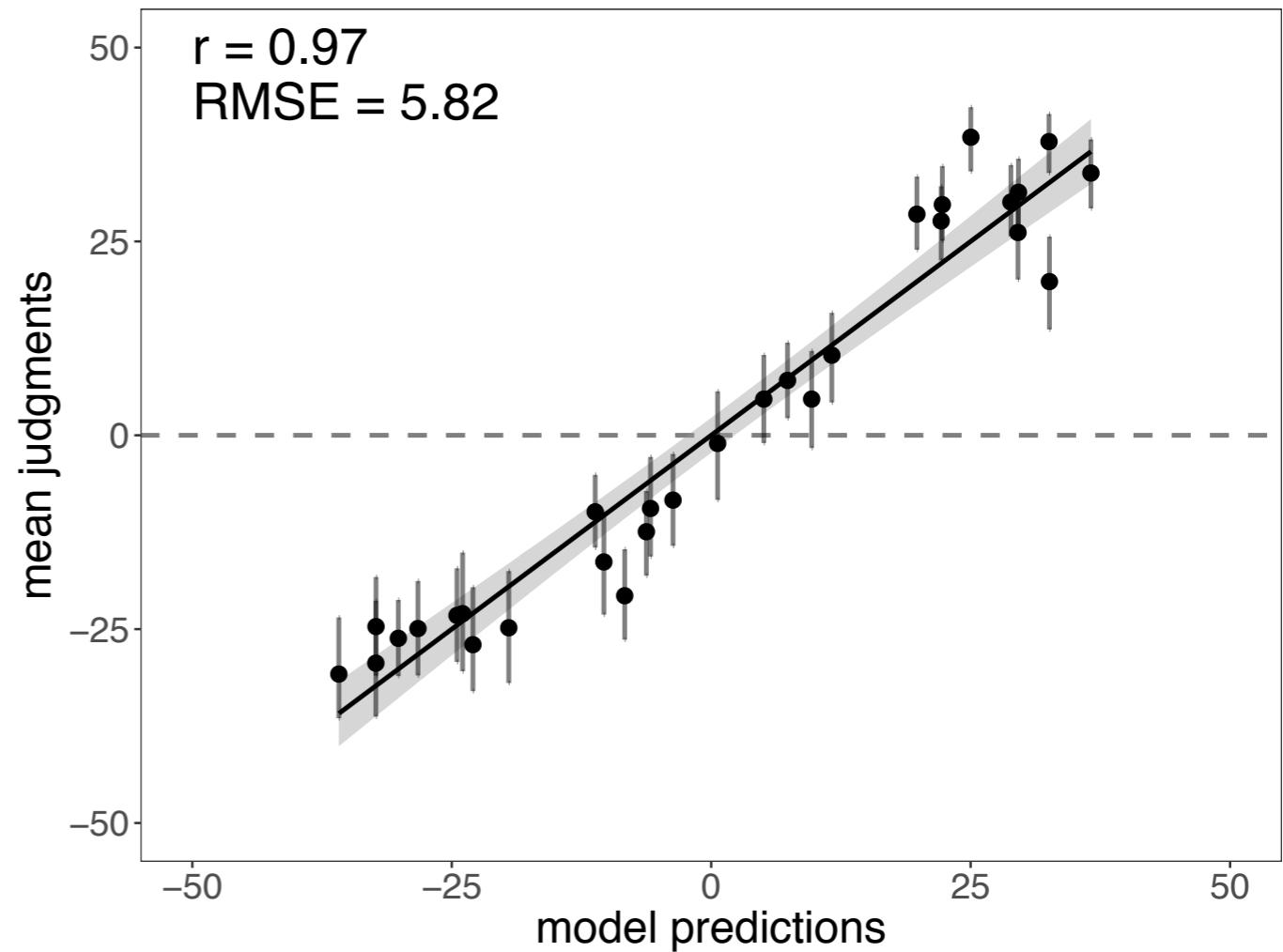
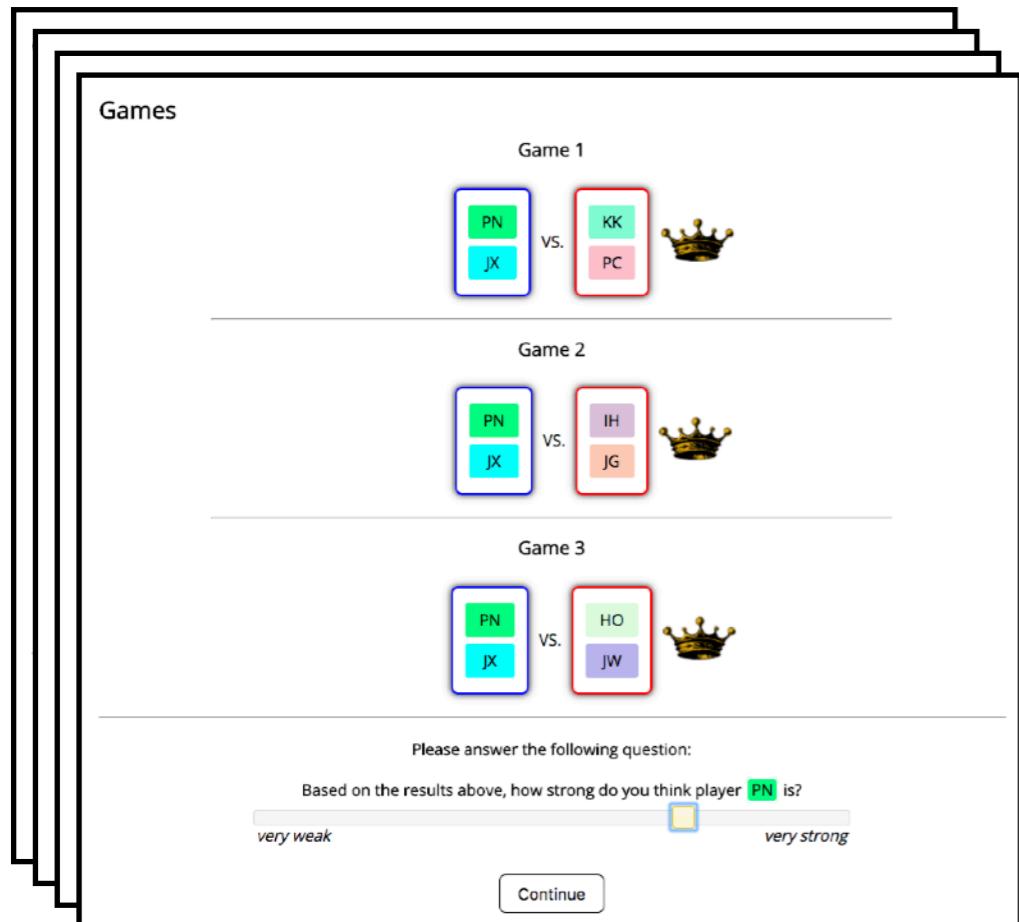
pulling

# A computational model of tug of war

```
var towModel = function() {
    var strength = mem(function (person) {return gaussian(50, 10)})  
  
    var lazy = function(person) {return flip(0.1) }  
  
    var pulling = function(person) {
        return lazy(person) ? strength(person) / 2 : strength(person) }  
  
    var totalPulling = function (team) {return sum(map(pulling, team))}  
  
    var winner = function (team1, team2) {
        totalPulling(team1) > totalPulling(team2) ? team1 : team2 }  
  
    var beat = function(team1,team2){winner(team1,team2) == team1}  
  
    condition(beat(['bob'], ['tom']))  
  
    return strength('bob')
}
```

# Experiment

## How strong is Player X?



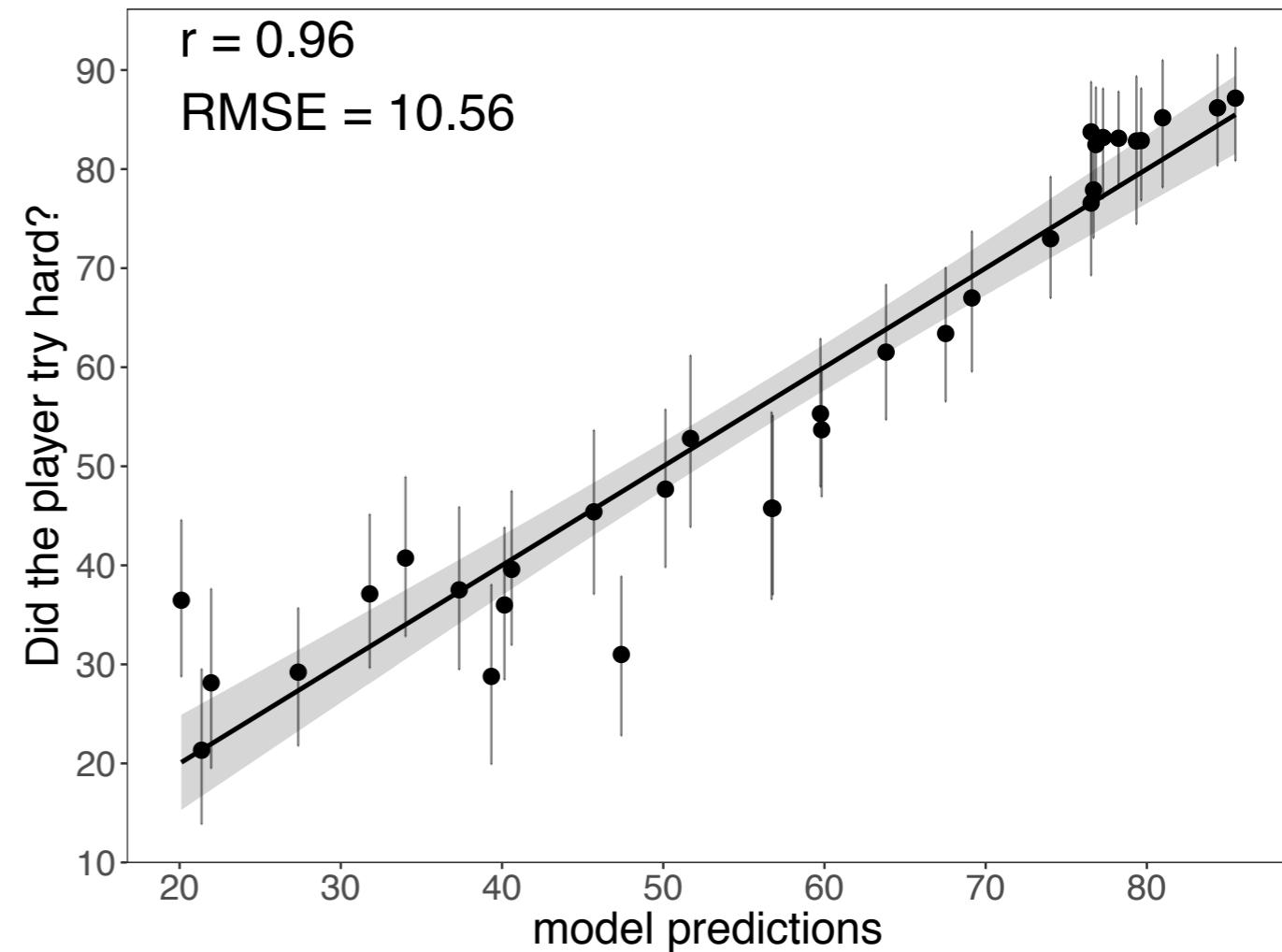
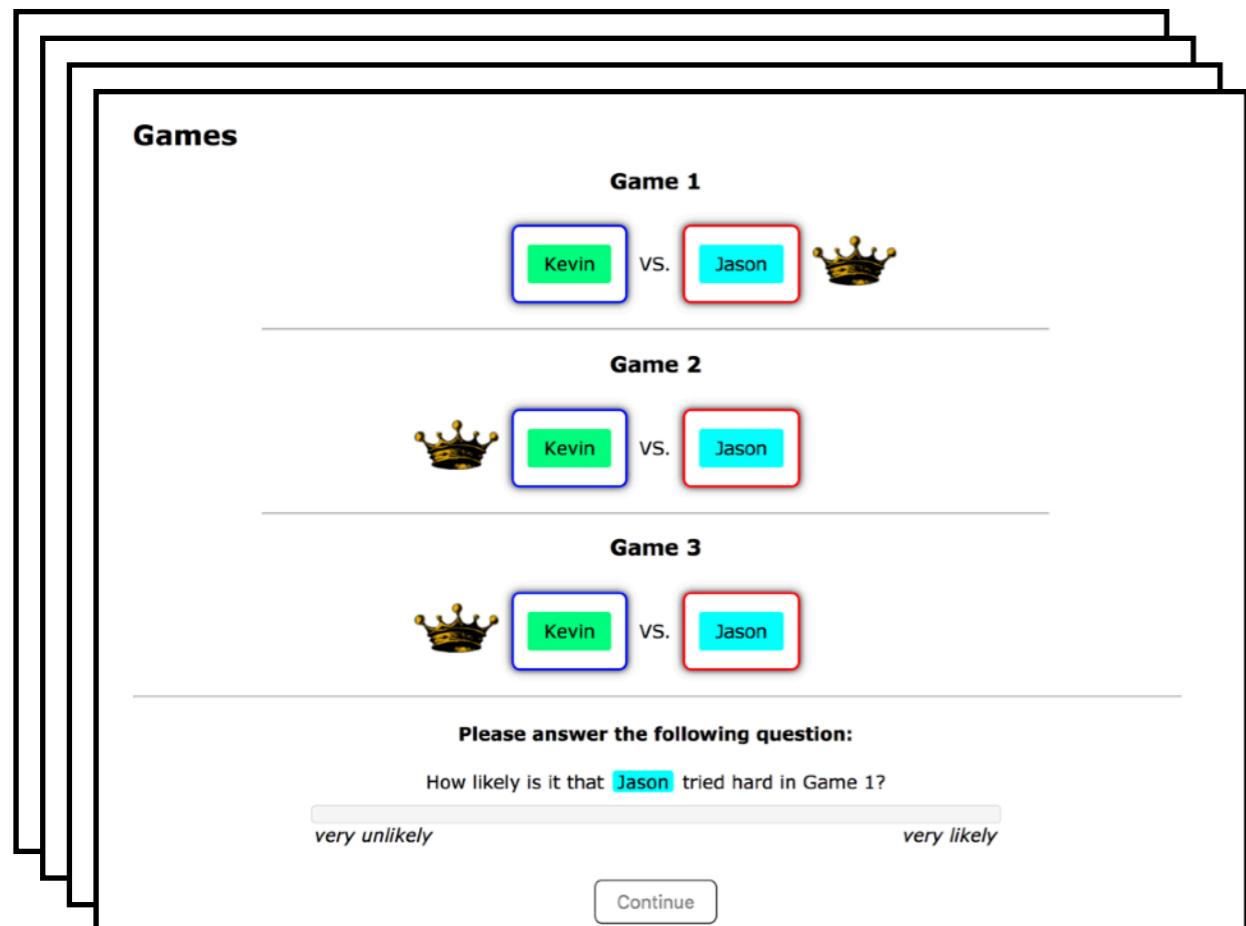
Gerstenberg & Goodman (2012) Ping Pong in Church: Productive use of concepts in human probabilistic inference. *Cognitive Science Proceedings*

Gerstenberg & Tenenbaum (2017) Intuitive Theories. *Oxford Handbook of Causal Reasoning*

Goodman, Tenenbaum, & Gerstenberg (2015) Concepts in a probabilistic language of thought. *The Conceptual Mind: New Directions in the Study of Concepts*

# Experiment

## Did player X try hard in Game 1?



Gerstenberg & Goodman (2012) Ping Pong in Church: Productive use of concepts in human probabilistic inference.  
Cognitive Science Proceedings

Gerstenberg & Tenenbaum (2017) Intuitive Theories. *Oxford Handbook of Causal Reasoning*

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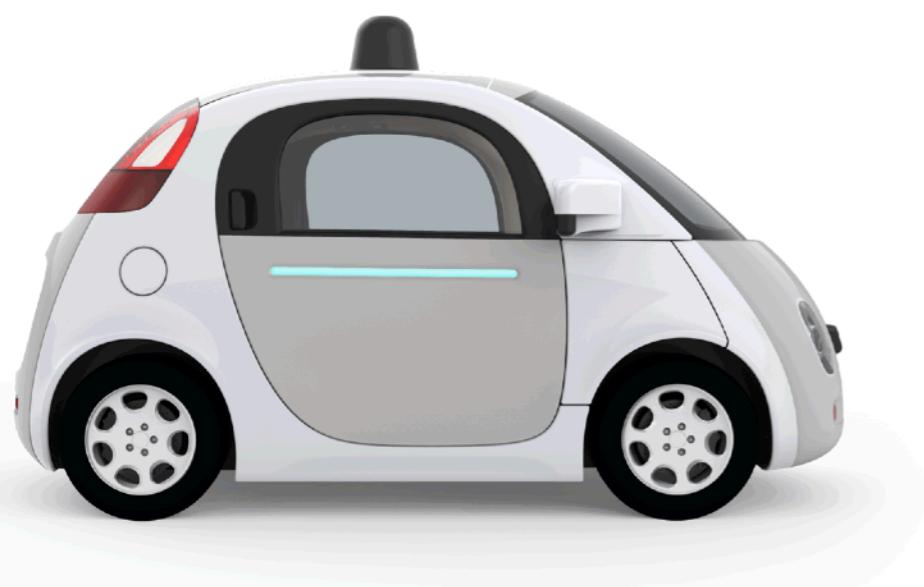
# Outline

- What is thought?
- What kind of a program?
- Probabilistic language of thought hypothesis
  - Compositionality
  - Productivity
- **Do it yourself!**
  1. WebPPL basics
  2. Building generative models
  3. Doing inference
- Questions, Resources, some cool examples

# What is thought?



How can we describe the intelligent  
inferences made in everyday human  
reasoning and learning?



How can we engineer  
intelligent machines?

# What is thought?

## Computational theory of mind



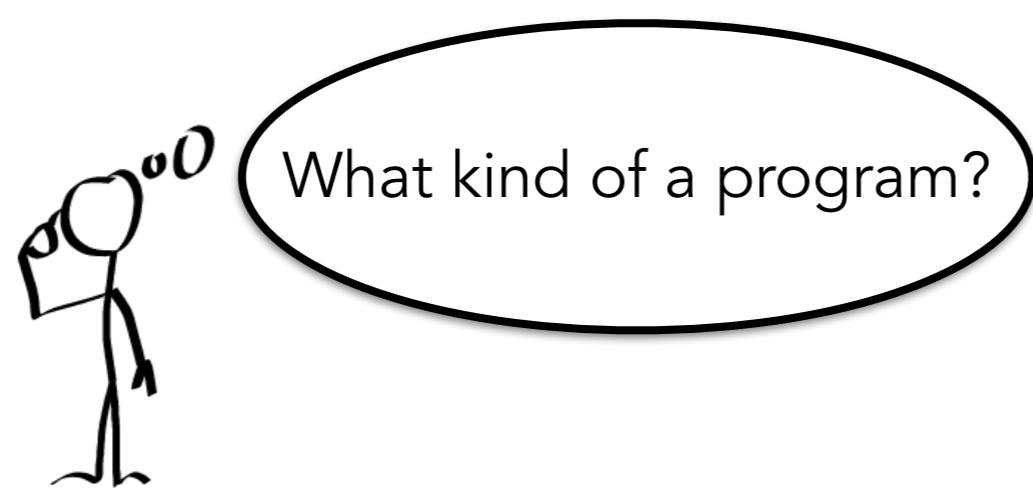
mind = computer

```
a.length;c++) {    0 ==  
& b.push(a[c]);    } ret  
function h() { for (var  
#User_logged").a(), a = q(  
place(/ +(?= )/g, ""), a =  
, b = [], c = 0;c < a.length;  
0 == r(a[c], b) && b.push(c);  
} c = {};  
= b.length - 1;  
} a = q(b), b = a(); b = a(b),  
c = 0;c < a.length;c++  
}
```

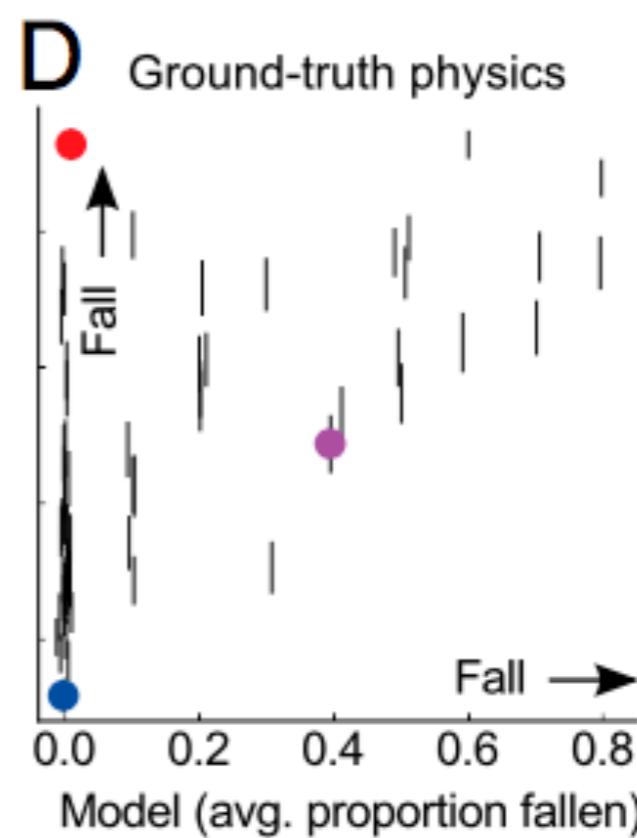
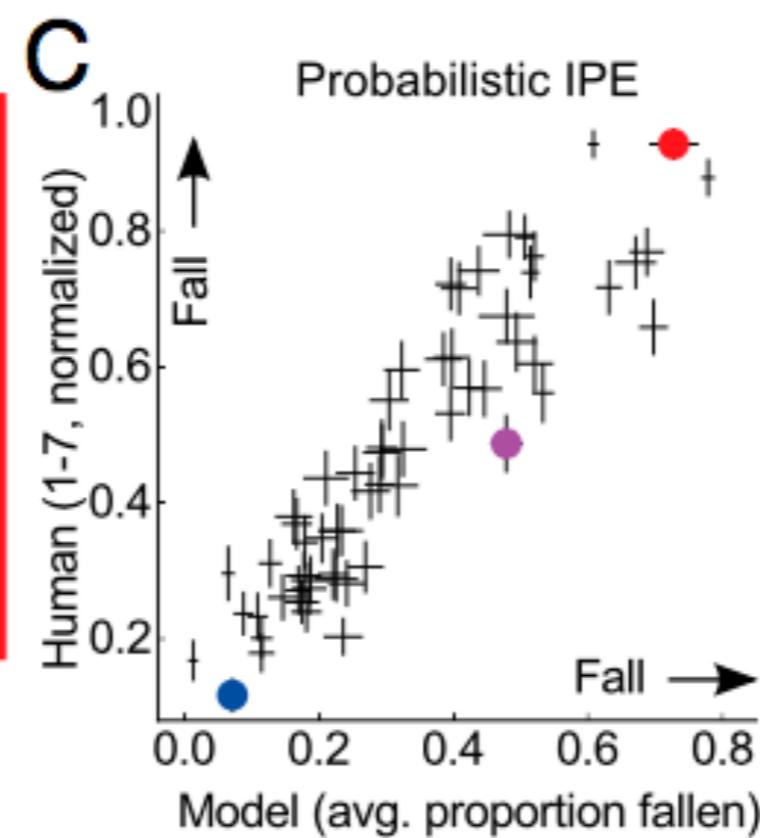
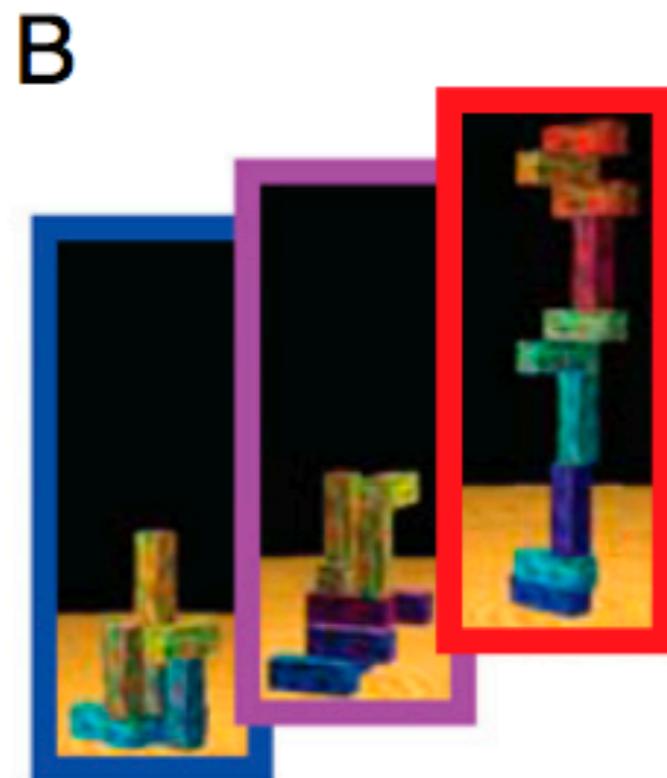
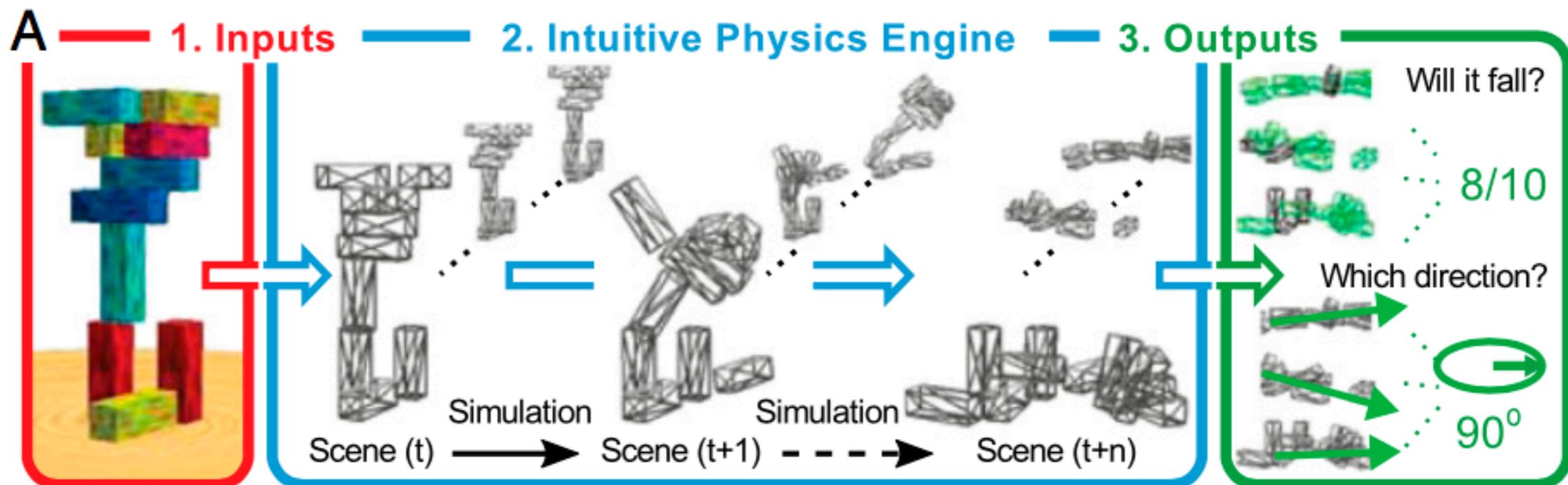
**run(program)**

mental representations =  
computer programs

thinking =  
running a program



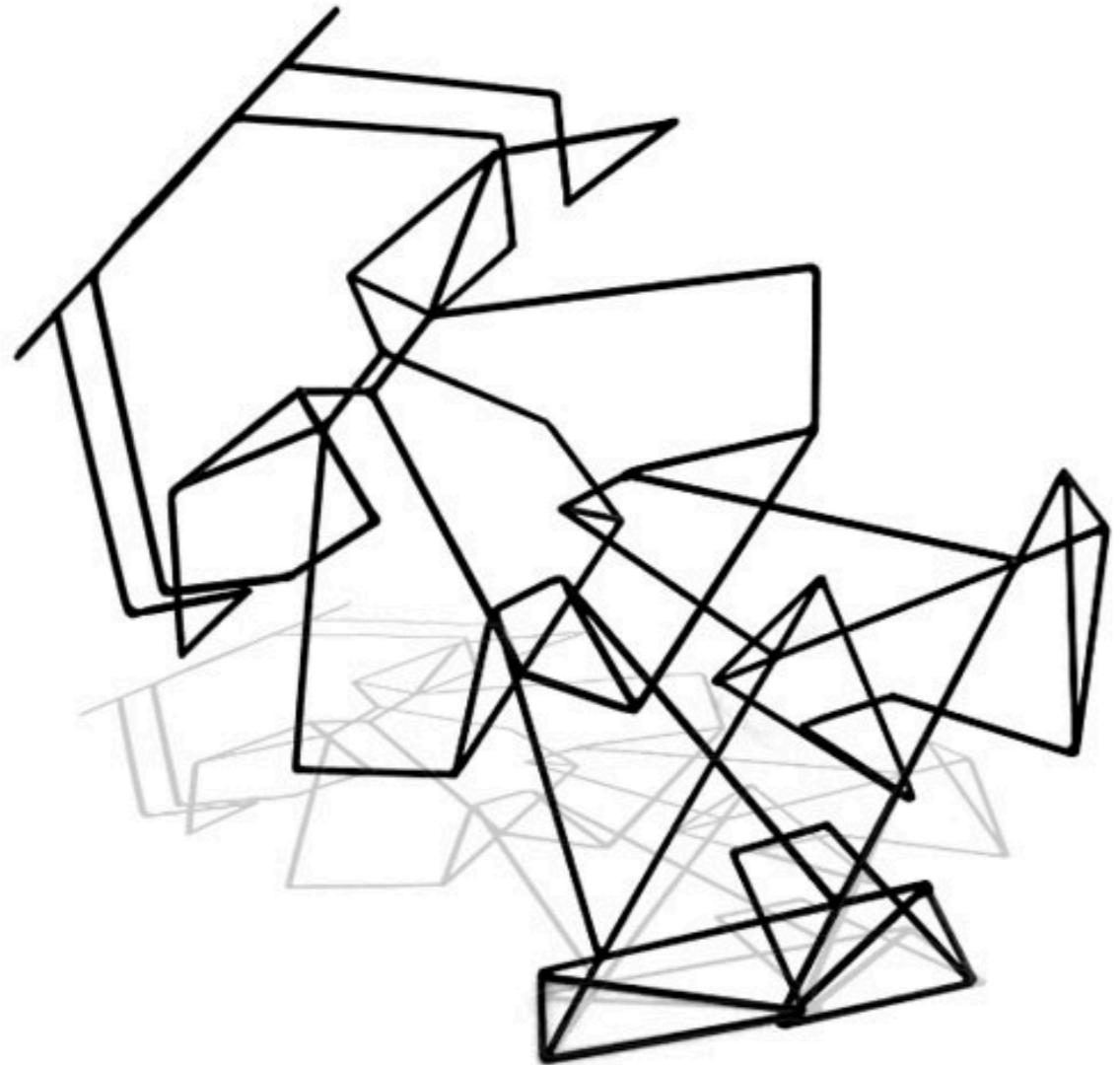
# What kind of a program?



Battaglia, Hamrick, & Tenenbaum (2013) Simulation as an engine of physical scene understanding.  
Proceedings of the National Academy of Sciences

# What kind of a program?

Structure



Knowledge

Probability



Uncertainty

# What kind of a program?

Structure

Probability

Logic

Rule-based systems

Neural networks

Knowledge

Uncertainty

# What kind of a program?

Structure

Probability

Logic

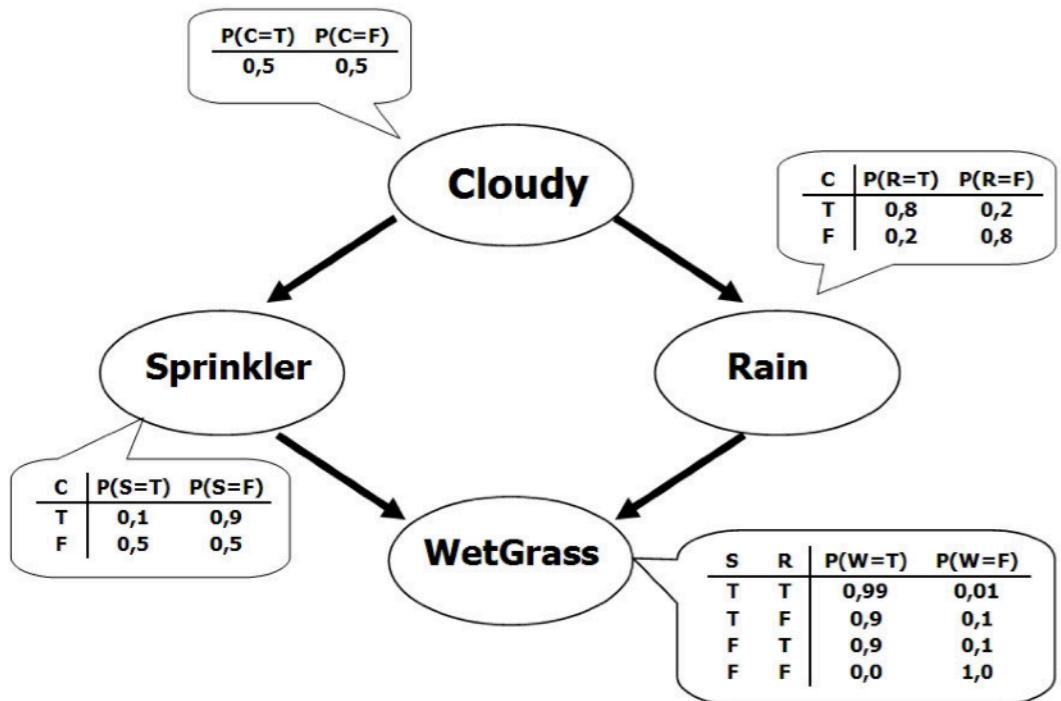
Rule-based systems

Neural networks

Probabilistic graphical models  
(Bayesian Networks)

Probabilistic programs

# What kind of a program?



```
var towModel = function() {
  var strength = mem(function (person) {return gaussian(50, 10)})

  var lazy = function(person) {return flip(0.1)}

  var pulling = function(person) {
    return lazy(person) ? strength(person) / 2 : strength(person) }

  var totalPulling = function (team) {return sum(map(pulling, team))}

  var winner = function (team1, team2) {
    totalPulling(team1) > totalPulling(team2) ? team1 : team2 }

  var beat = function(team1,team2){winner(team1,team2) == team1}

  condition(beat(['bob'], ['tom']))

  return strength('bob')
}
```

## (Causal) Bayesian networks

- have “thick arrows”
- limited expressiveness
- relationships between events / propositions

## Probabilistic programs

- have rich compositionality
- provide a complete specification of the domain (nothing hidden behind arrows)
- support productive inferences
- support reasoning about events, properties, agents, objects, ...

# Probabilistic language of thought hypothesis

## Informal version:

"Concepts have a language-like compositionality and encode probabilistic knowledge. These features allow them to be extended productively to new situations and support flexible reasoning and learning by probabilistic inference."

Fodor (1975). The language of thought

Goodman, Tenenbaum, & Gerstenberg (2015) Concepts in a probabilistic language of thought. *The Conceptual Mind: New Directions in the Study of Concepts*

# Probabilistic language of thought hypothesis

## Informal version:

"Concepts have a language-like **compositionality** and encode probabilistic knowledge. These features allow them to be extended **productively** to new situations and support flexible reasoning and learning by **probabilistic inference**."



### Productivity

"infinite use of finite means"  
(Wilhelm von Humboldt)

### Language

limited number of letters  
fixed set of grammatical rules  
can express an infinite number of thoughts

# Probabilistic programs

D  
I  
Y  
O U R S E L F

# Why WebPPL?

## WebPPL

## other PPLs

- written by cognitive scientists for cognitive scientists
- goal: building computational models of cognition
- extremely flexible
- can be slow

- Stan, Anglican, Alchemy, BUGS, Edward, PyMC
- goal: building rich models for data analysis
- flexible but limited
- faster (for the models that can be expressed)

1. WebPPL basics
2. Building generative models
3. Doing inference

<http://bit.do/webppl>

# 1. WebPPL basics

# WebPPL basics

- declare variables
- data formats: numbers, strings, logicals, objects, arrays
- if-then-statements
- defining functions
- higher order functions
  - map
  - repeat

# WebPPL basics



- WebPPL = purely functional programming language
  - **can't** write `for` loops or `while` statements
  - **can** create higher-order functions and recursive functions
  - for example: `map` = apply a function to each element of a list (like a `for` loop)

## 2. Building generative models

# Building generative models

- forward sampling and random primitives
- building simple models
- sample from probability distributions
- memoization: `mem`
- recursive functions

# Building generative models



- WebPPL is a language to formally describe how the world works
- random choices capture our uncertainty or ignorance
- the language is **universal**: it can express any computable process
- causal dependence is important: the program describes what influences what

Stuhlmüller, Tenenbaum, & Goodman (2010) Learning Structured Generative Concepts. Cognitive Science Proceedings

Stuhlmüller & Goodman (2014) Reasoning about reasoning by nested conditioning: Modeling theory of mind with probabilistic programs. Cognitive Systems Research

# Building generative models



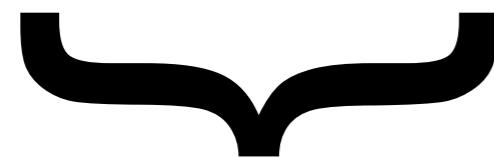
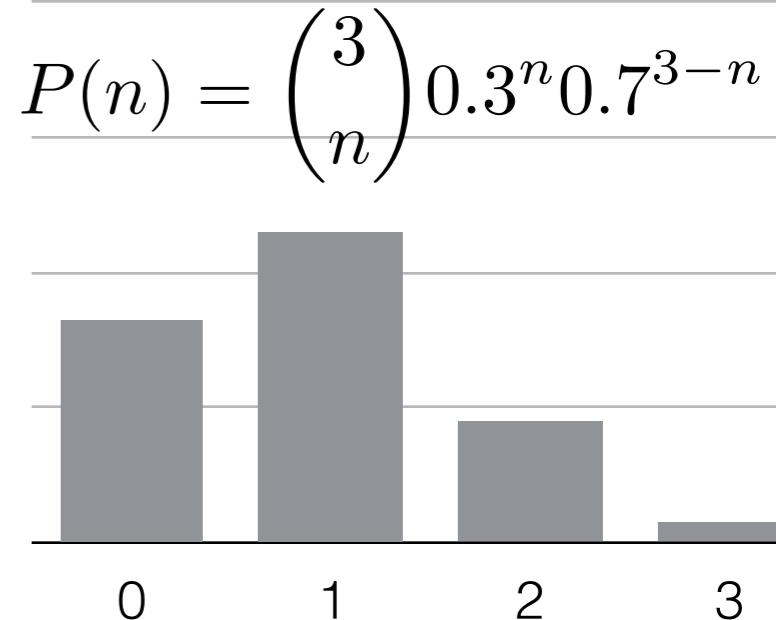
relationship between sampling and probability distributions

Random primitives:

```
var a = flip(0.3)  
var b = flip(0.3)  
var c = flip(0.3)  
return a + b + c
```

=> 1 0 0  
=> 0 0 0  
=> 1 0 1  
=> 2 0 1  
...

probability / frequency



Sampling



Distributions

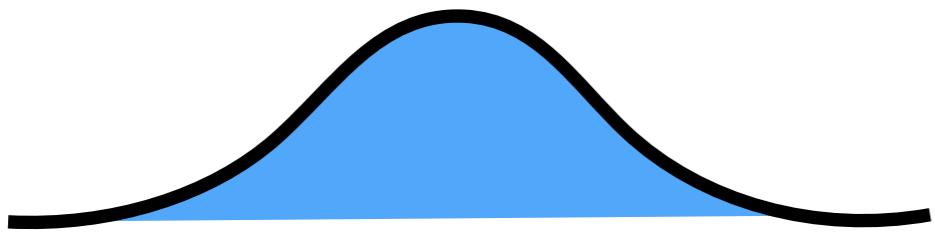
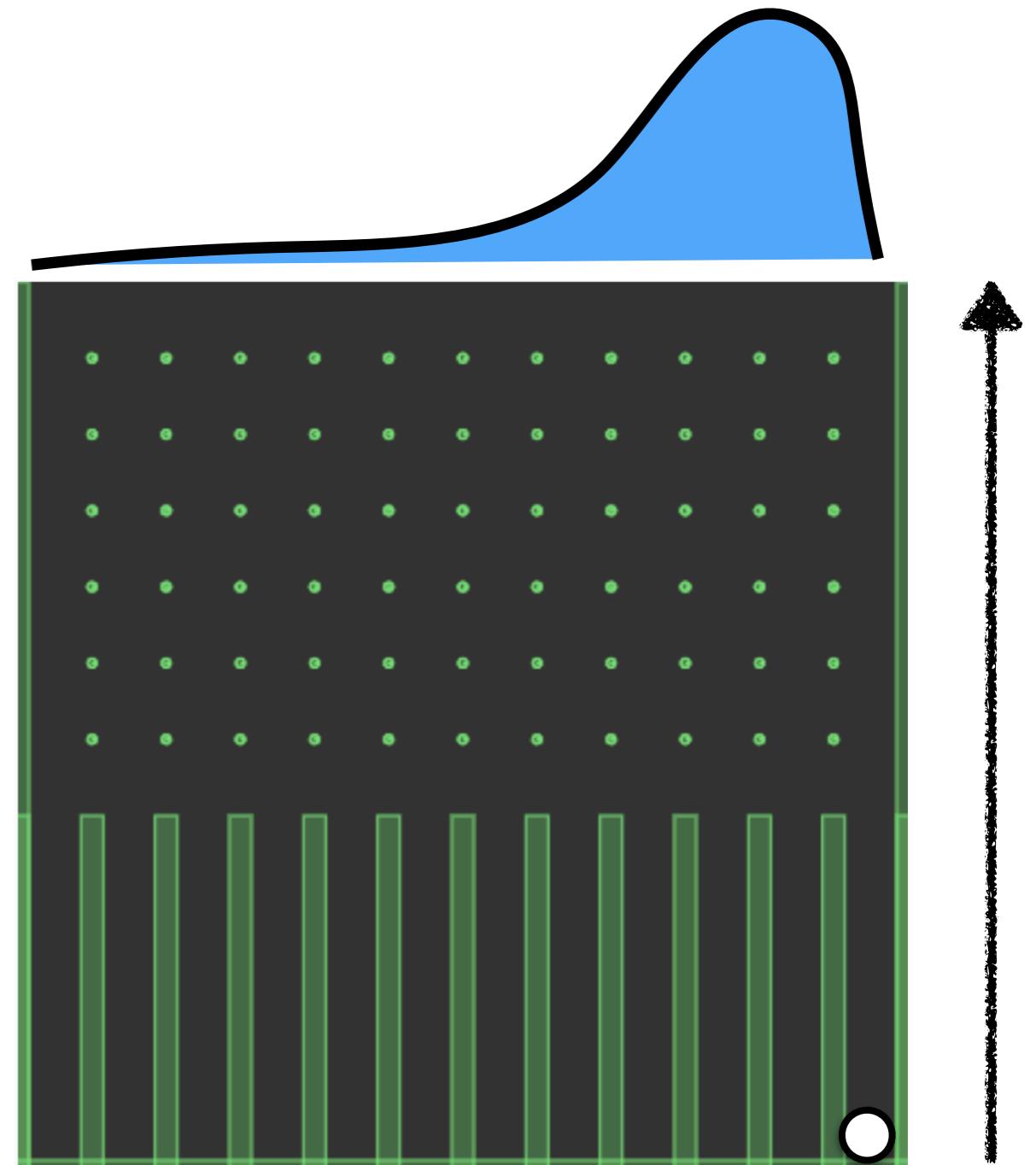
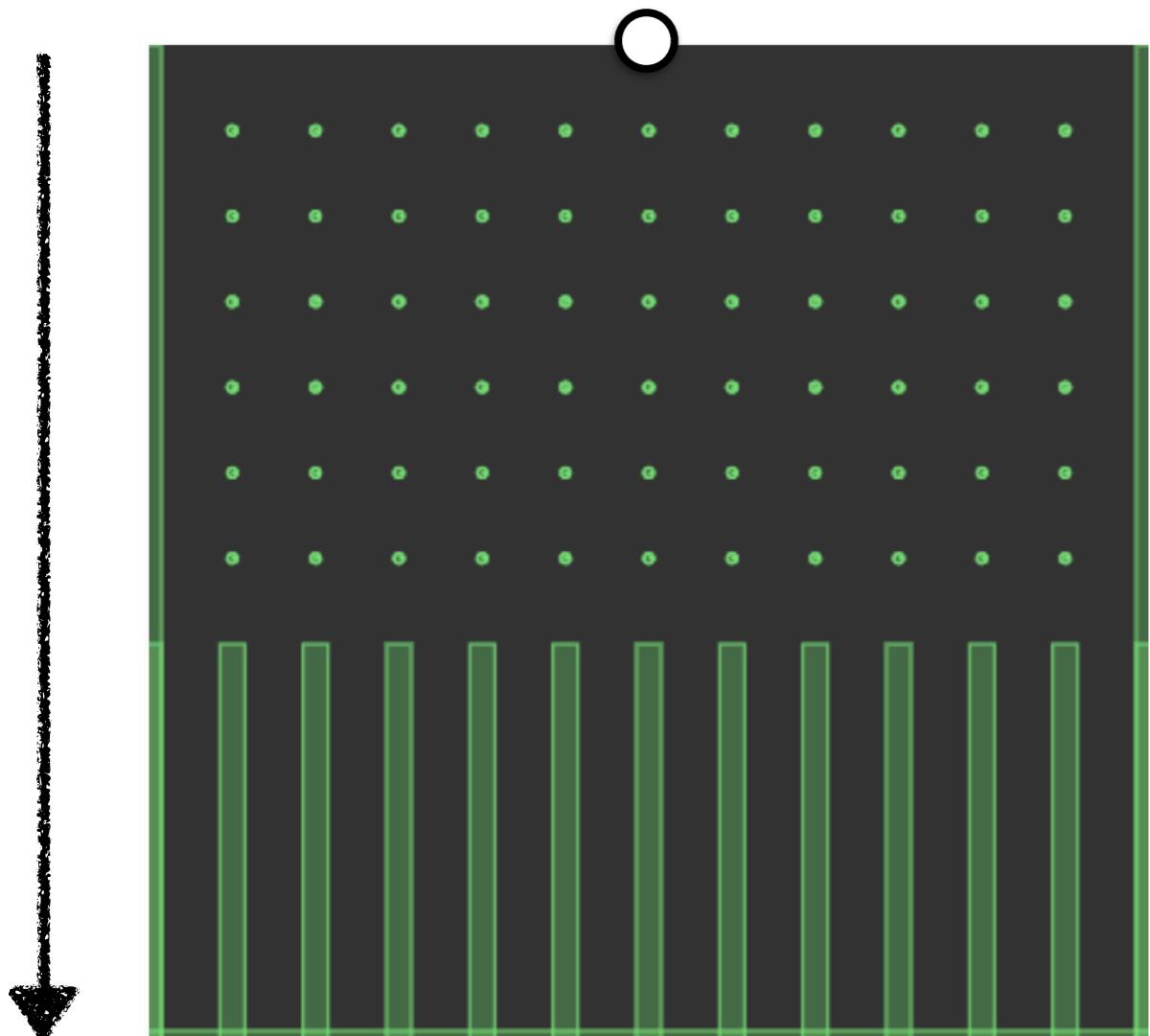
any computable distribution can be represented as the distribution induced by sampling from a probabilistic program

# 3. Doing inference

# Doing inference

Run forward

Where will the ball land?



Reason backward  
Where did the ball come from?

# Doing inference

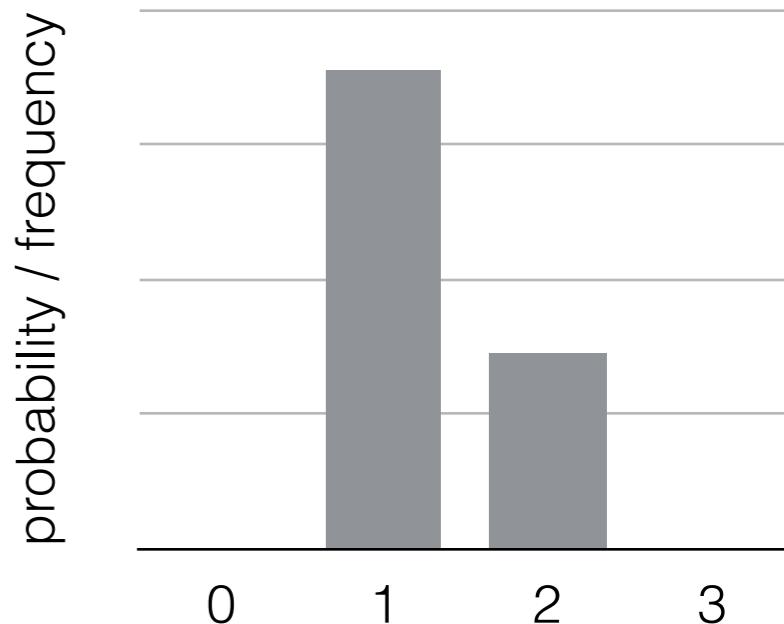
## Conditional inference:

Infer(

```
function() {  
    var a = flip(0.3)  
    var b = flip(0.3)  
    var c = flip(0.3)  
    condition(a + b == 1)  
    return a + b + c})
```

=> 1 0 0 0 1  
=> 0 0 0 0 0  
=> 1 0 1 0 0  
=> T F F T 1  
=> 2 0 1 1 1

Posterior distribution



“It is an old maxim of mine that when you have excluded the impossible, whatever remains, however improbable, must be the truth.”

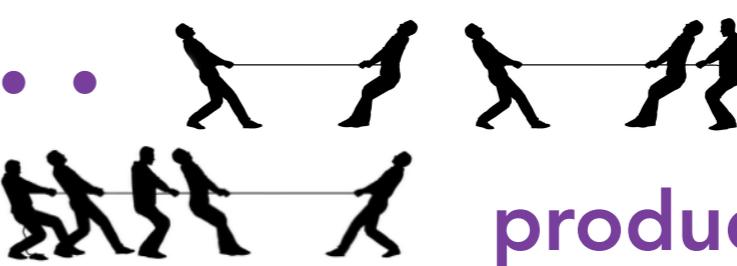


# Doing inference



- conditioning on variables
  - rejection sampling
  - WebPPL's inference procedures
- conditioning on arbitrary expressions
- other inference procedures
- **forward, rejection, enumerate, MH, ...**
- you don't have to worry about inference. **very nice!**
- WebPPL allows us to parsimoniously describe rich generative model structures and explore the inference patterns that emerge from the interaction of model and data

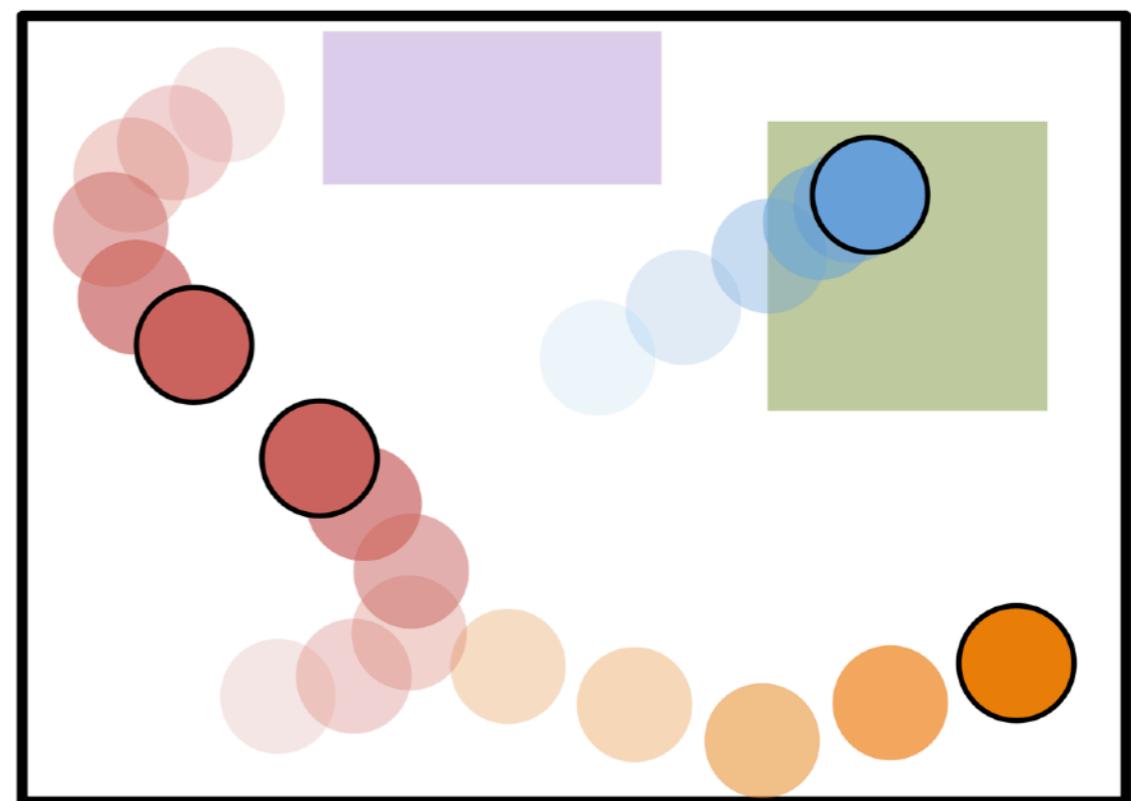
"Concepts have a language-like **compositionality** and encode probabilistic knowledge. These features allow them to be extended **productively** to new situations and support flexible reasoning and learning by **probabilistic inference**."

```
var towModel = function() {  
    var strength = mem(function (person) {return gaussian(50, 10)})  
  
    var lazy = function(person) {return flip(0.1)} compositionality  
  
    var pulling = function(person) {  
        return lazy(person) ? strength(person) / 2 : strength(person)  
    }  
  
    var totalPulling = function (team) {return sum(map(pulling, team))}  
  
    var winner = function (team1, team2) {  
        totalPulling(team1) > totalPulling(team2) ? team1 : team2 }  
  
    var beat = function(team1,team2){winner(team1,team2) == team1}  
  
    condition(beat(['bob'], ['tom'])) . . .   
    return strength('bob') . . . productivity  
}
```

# Some more cool examples: Program induction

	(i)	(ii)	(iii)
<b>Level N</b>	Innate concepts	<i>Entity</i>	<pre>(define (make-entity property1 property2 ... )       (list property1 property2 ... ))</pre>
		<i>Newtonian Dynamics</i>	<pre>(define (run-dynamics entities forces                            init-cond steps dt)   (if (= steps 0) '()       (let* ((m (get-mass entities))              (F (apply-forces forces entities))              (a (/ F m)))         (new-cond (integrate init-cond                                a dt noise)))       (pair new-cond (run-dynamics entities                                      forces new-cond (- 1 step) dt))))</pre>
<b>Level 2</b>	Entity types	<i>Puck:</i> ○	<pre>(define puck (make-entity                pos shape mass vel ... ))</pre>
		<i>Surface:</i> □	<pre>(define surface (make-entity                   pos shape friction ... ))</pre>
	Properties	<i>Mass</i>	<pre>(define (mass)       (pair "mass" (uniform '(1 3 9)))))</pre>
		<i>Friction</i>	<pre>(define (friction)       (pair "friction" '(uniform '(0 5 20)))))</pre>
	Force classes	<i>Pairwise:</i> ○ ↗	<pre>(define (pairwise-force c1 c2)   (let* ((a (uniform-draw '(-1 0 1))))     (lambda (o1 o2)       (let ((r (euc-dist o1 o2)))         (/ (* a del(o1,col(o1)) del(o2,col(o2)))             (power r 2))))))</pre>
		<i>Global:</i> ○ →	<pre>(define (global-force)   (let* ((d (uniform-draw compass-dir)))     (lambda (o) (* k d))))</pre>
<b>Level 1</b>	Property values	<ul style="list-style-type: none"> <li>● : large mass</li> <li>○ : medium mass</li> <li>■ : small mass</li> <li>■ : high friction</li> <li>■ : no friction</li> </ul>	<pre>(define world-entities   (map sample-values entity-list))</pre>
	Force parameters	Force b/w reds: attract	<pre>(define world-forces   (map sample-parameters force-list))</pre>
<b>Level 0 (data)</b>	Initial conditions		<pre>(define scenario   (let* (     (init-cond (sample-init world-entities))     (run-dynamics world-entities                  world-forces init-cond steps dt)))     ...))</pre>

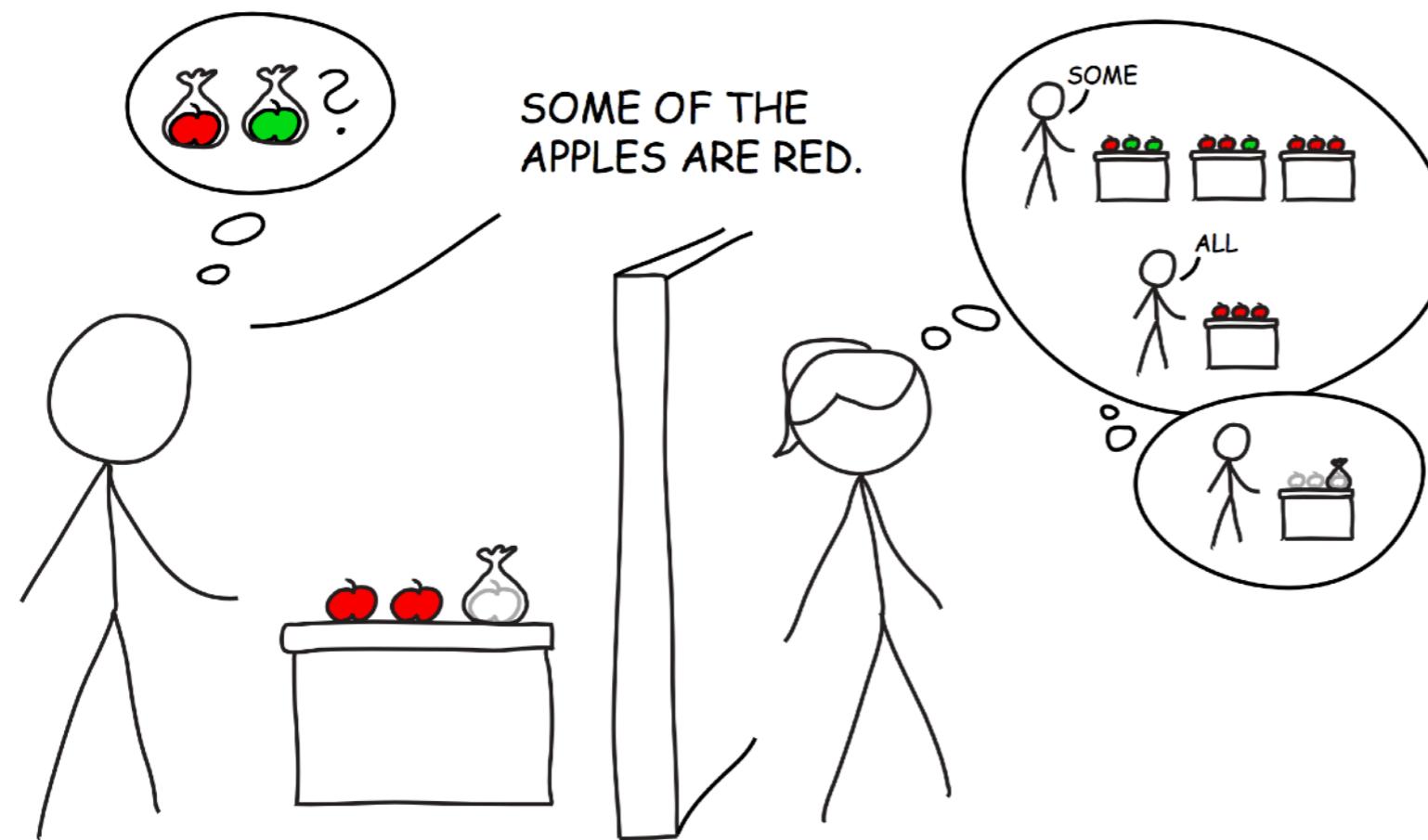
Learning at theory of physics



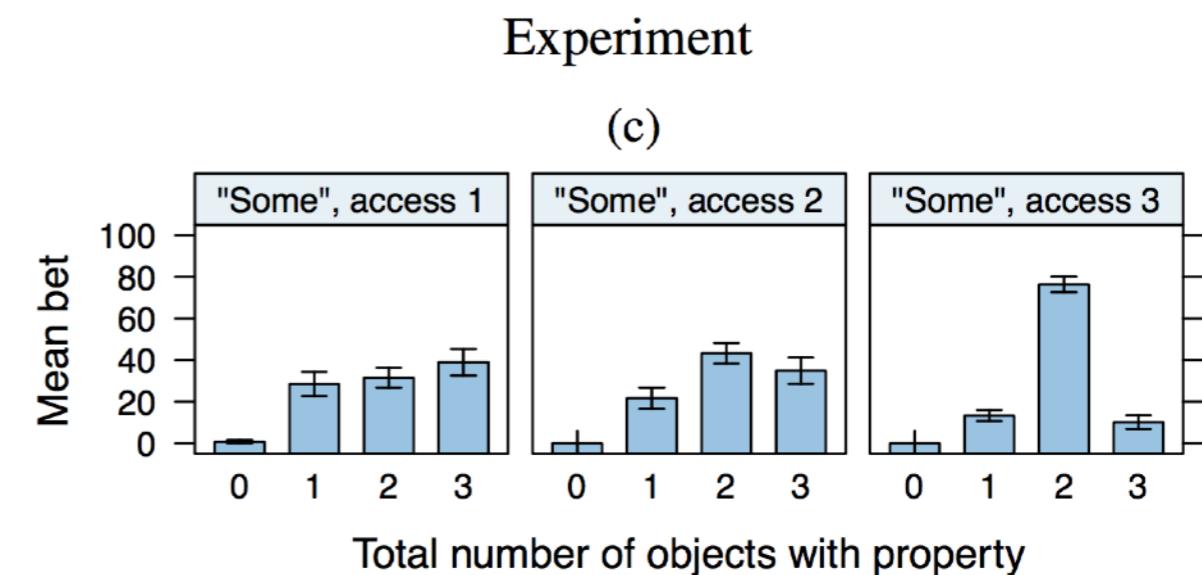
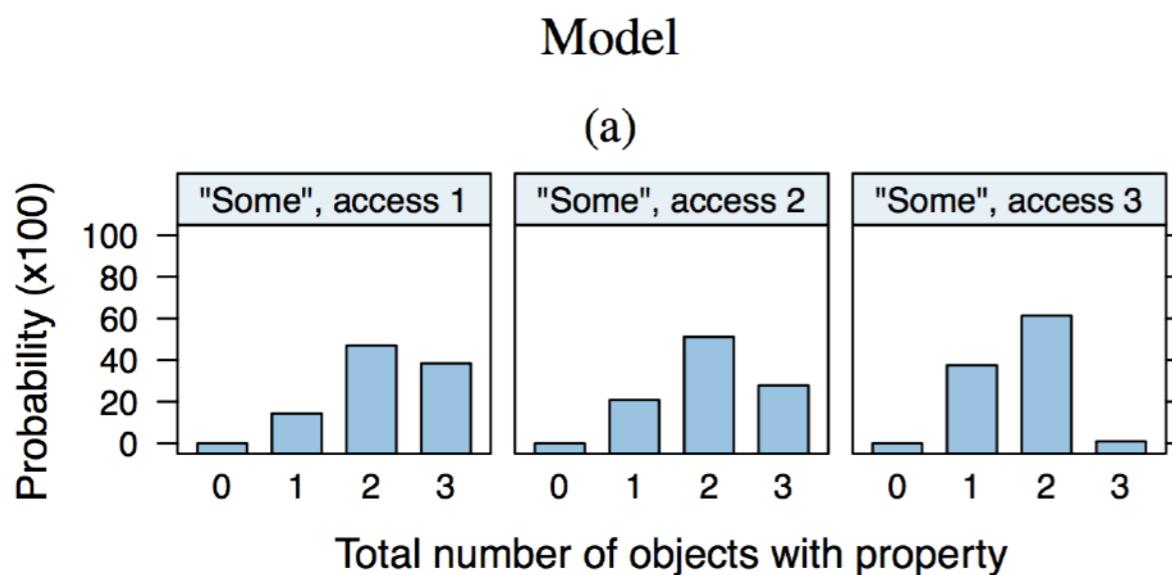
Ullman, Stuhlmüller, Goodman, & Tenenbaum (2014) Learning physics from dynamical scenes. Cognitive Science Proceedings

Ullman, Stuhlmüller, Goodman, & Tenenbaum (in press) Learning physical parameters from dynamic scenes. Cognitive Psychology

# Some more cool examples: Pragmatic inference



Scalar implicature  
("some" but not "all")



Goodman & Stuhlmüller (2013) Knowledge and implicature: Modeling language understanding as social cognition. Topics in Cognitive Science

# Resources: theory

- Goodman, Mansinghka, Roy, Bonawitz, & Tenenbaum (2008) Church: A language for generative models. *Uncertainty in Artificial Intelligence*
  - ➔ [https://stanford.edu/~ngoodman/papers/churchUAI08\\_rev2.pdf](https://stanford.edu/~ngoodman/papers/churchUAI08_rev2.pdf)
- Goodman, Tenenbaum, & Gerstenberg (2015) Concepts in a probabilistic language of thought. *The Conceptual Mind: New Directions in the Study of Concepts*
  - ➔ [web.mit.edu/tger/www/papers/Concepts in a probabilistic language of thought  
\(Goodman, Tenenbaum, Gerstenberg, 2014\).pdf](http://web.mit.edu/tger/www/papers/Concepts_in_a_probabilistic_language_of_thought_(Goodman,_Tenenbaum,_Gerstenberg,_2014).pdf)
- Freer, Roy, & Tenenbaum (2012) Towards common-sense reasoning via conditional simulation: legacies of Turing in Artificial Intelligence. arXiv preprint arXiv:1212.4799
  - ➔ <https://arxiv.org/pdf/1212.4799.pdf>
- Lake, Ullman, Tenenbaum, & Gershman (2016) Building machines that learn and think like people. arXiv preprint arXiv:1604.00289
  - ➔ <https://arxiv.org/pdf/1604.00289.pdf>
- Gerstenberg & Tenenbaum (2017) Intuitive Theories. *Oxford Handbook of Causal Reasoning*
  - ➔ [web.mit.edu/tger/www/papers/Intuitive Theories, Gerstenberg, Tenenbaum, 2017.pdf](http://web.mit.edu/tger/www/papers/Intuitive_Theories,_Gerstenberg,_Tenenbaum,_2017.pdf)
- Chater & Oaksford (2013) Programs as causal models: Speculations on mental programs and mental representation. *Cognitive Science*
  - ➔ <http://onlinelibrary.wiley.com/doi/10.1111/cogs.12062/abstract>
- Ghahramani (2015) Probabilistic machine learning and artificial intelligence. *Nature*
  - ➔ <http://www.nature.com/nature/journal/v521/n7553/full/nature14541.html>

# Resources: practice

- <https://probmods.org/>
  - many more cool chapters to play around with
- <http://webppl.org/>
  - Editor to play around with code
- <http://dippl.org/>
  - Details about WebPPL
- <https://github.com/probmods/webppl>
  - github repository with latest developments
- <http://webppl.readthedocs.io/en/master/>
  - function reference for the webppl language
- <http://agentmodels.org/>
  - Great web book that focuses on how to model agents and inferences about agents
- <http://probabilistic-programming.org/wiki/Home>
  - homepage comparing different probabilistic programming languages

# Thanks !

[http://bit.do/webppl\\_feedback](http://bit.do/webppl_feedback)



CENTER FOR  
**Brains**  
Minds +  
Machines