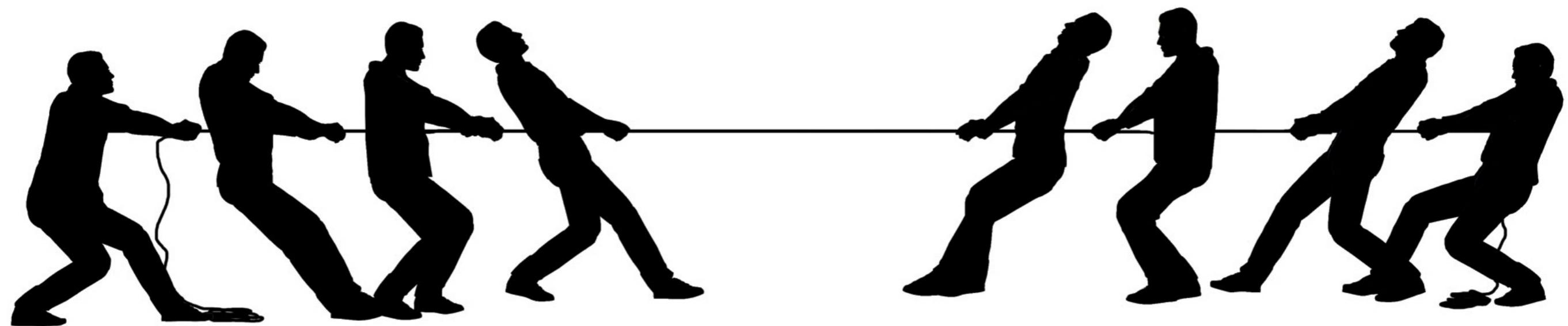
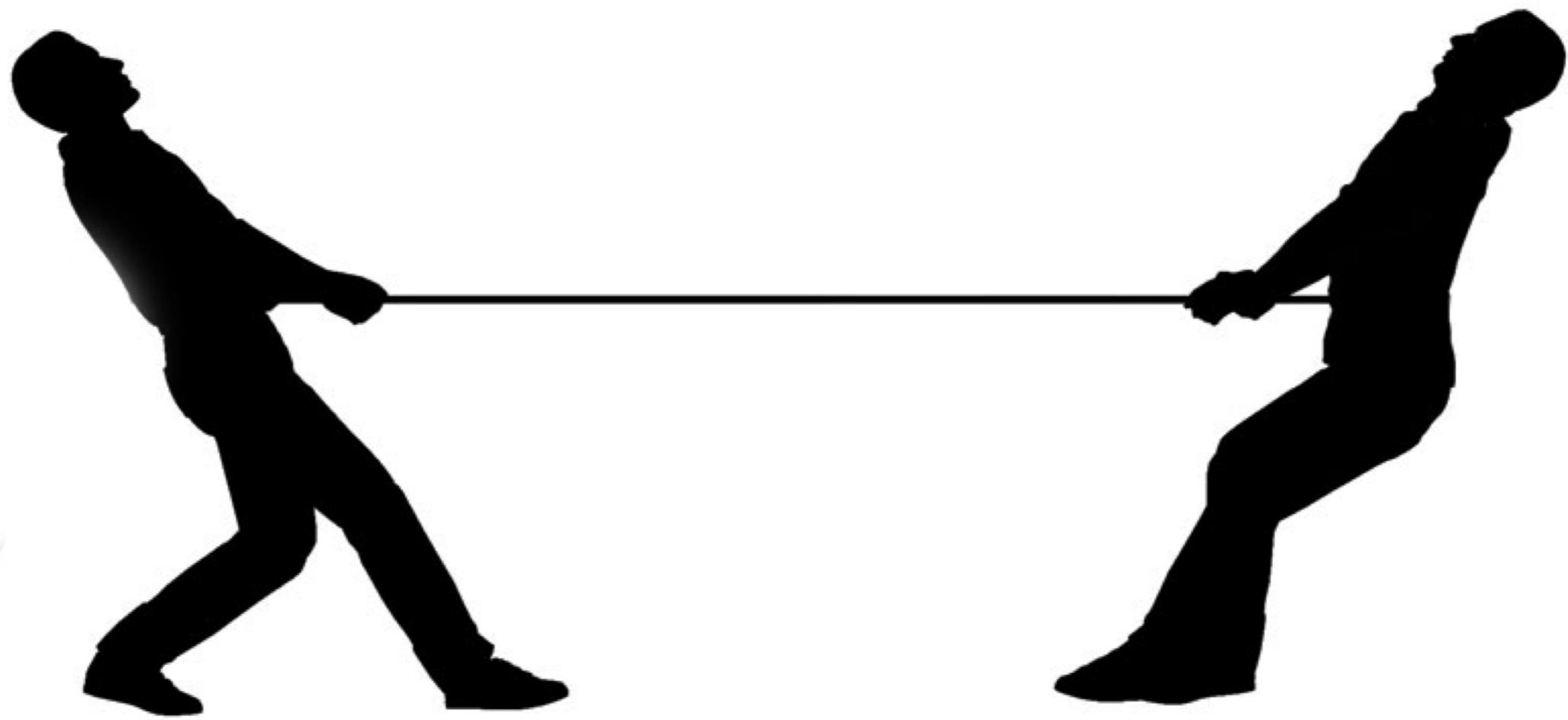


WebPPL Recitation



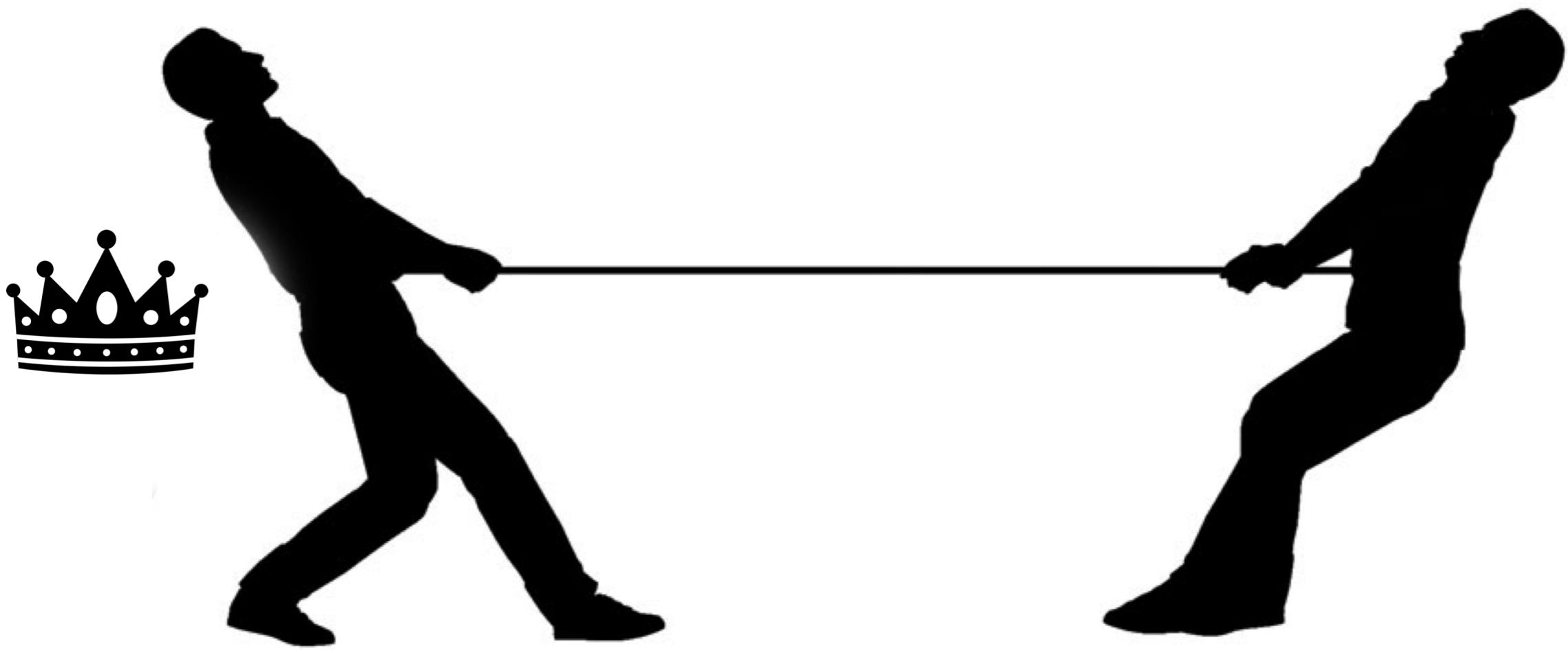
Tug of War





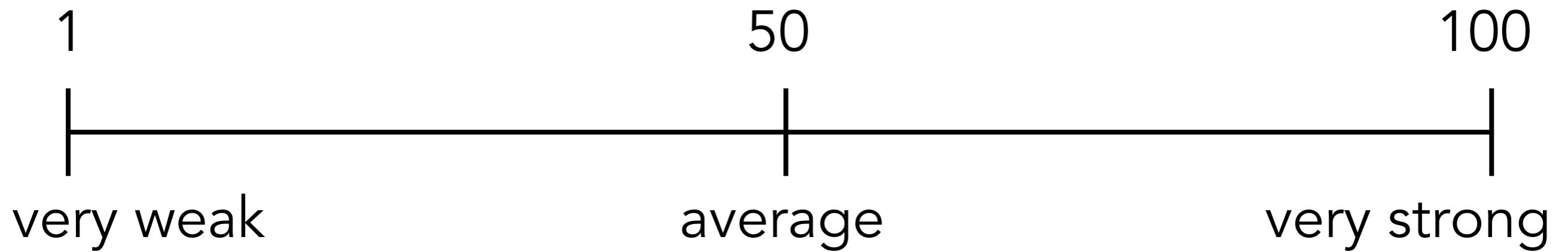
Tom

Steve



Tom

Steve





Sam



Mark

Nick

1

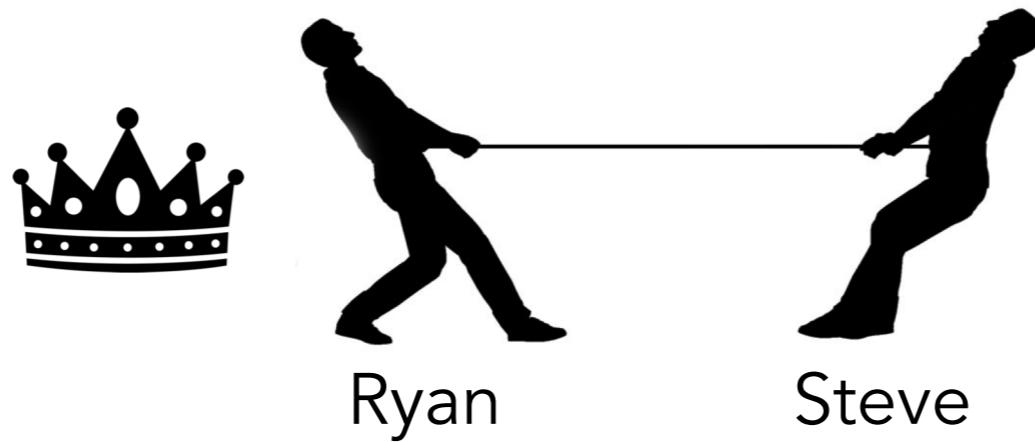
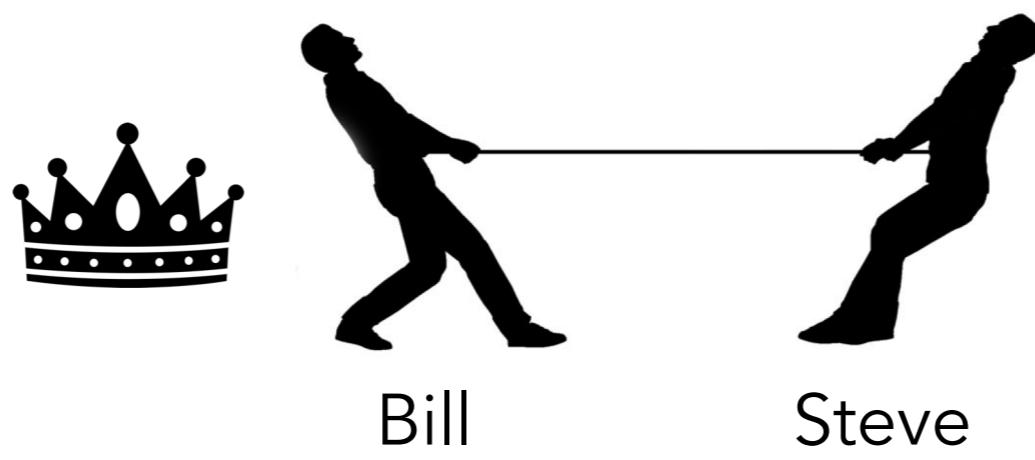
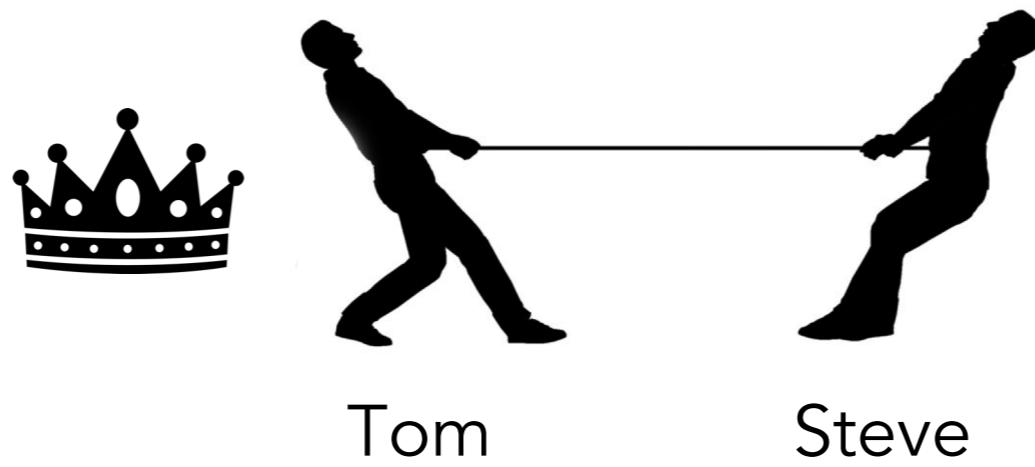
50

100

very weak

average

very strong



1

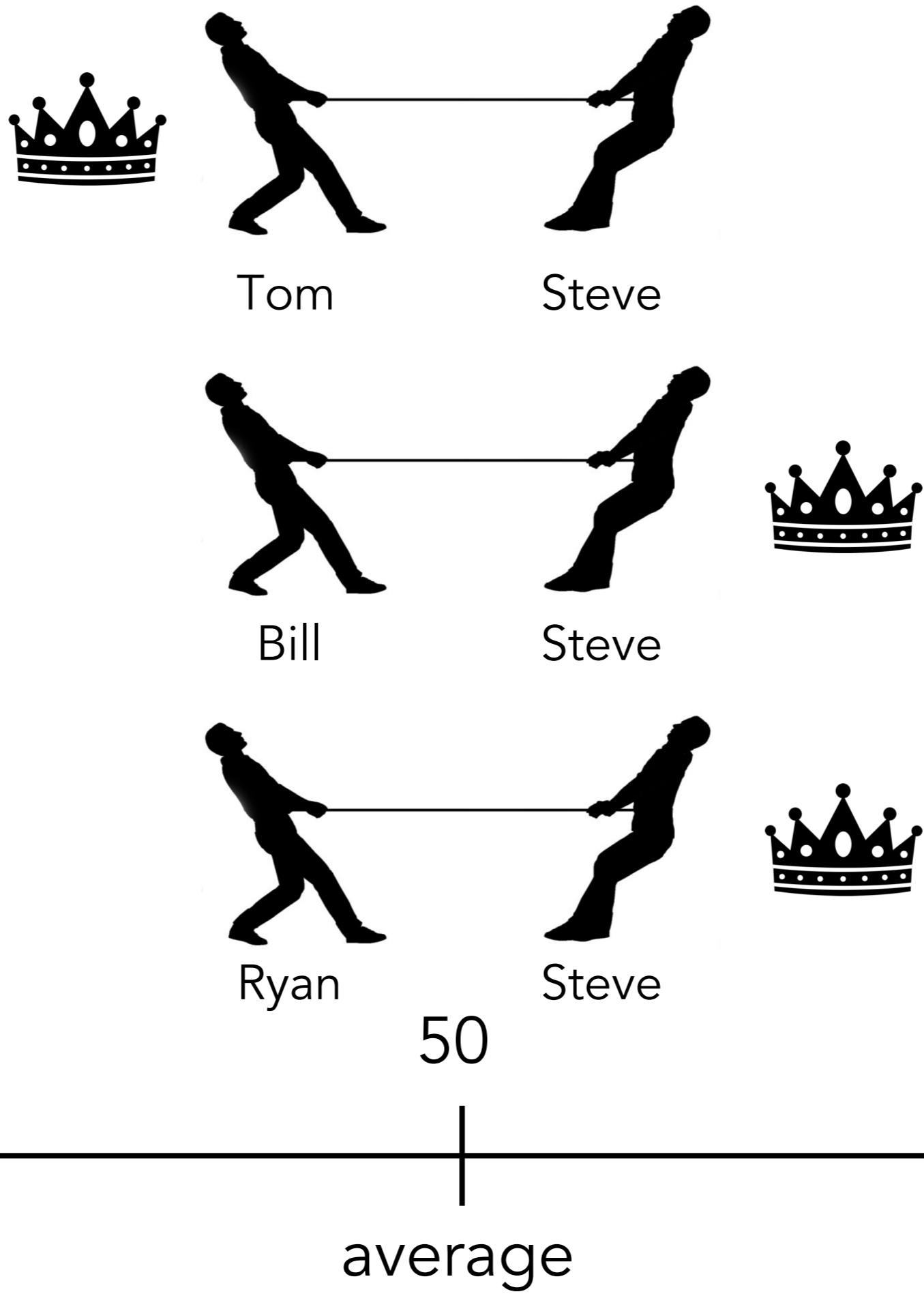
50

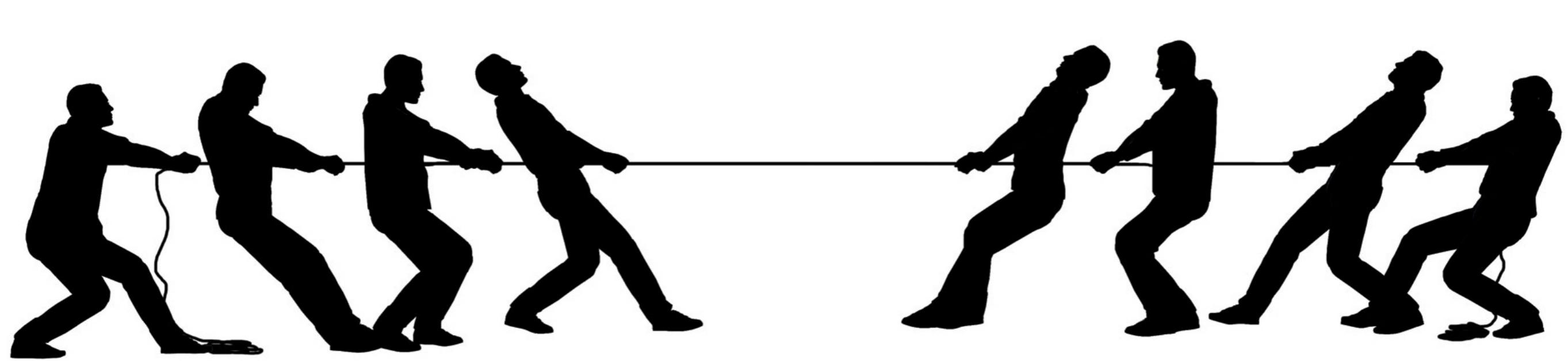
100

very weak

average

very strong





Concepts:

teams
person
strength
effort
pulling
winner

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?

Games

Game 1
PN vs. KK, PC

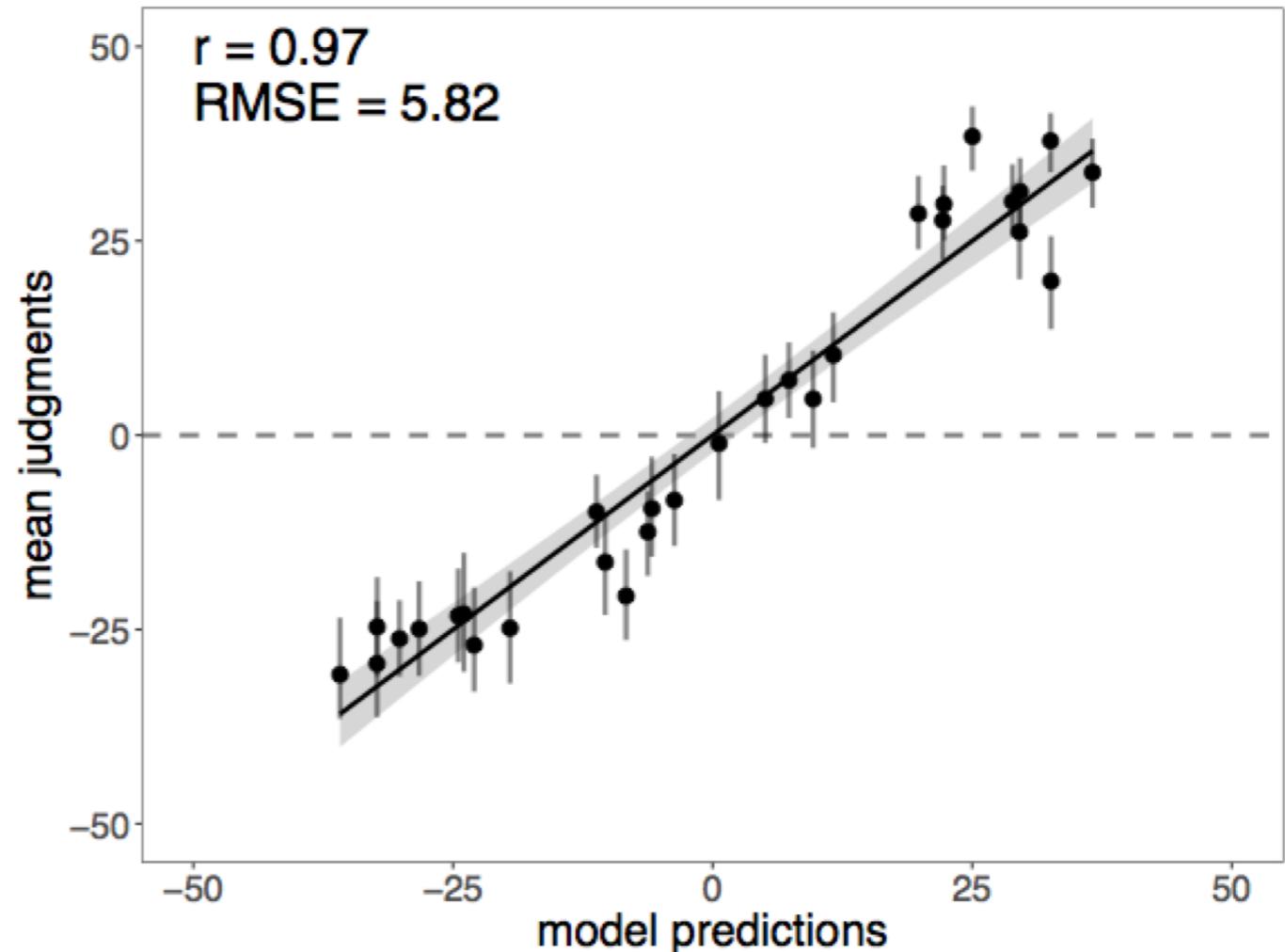
Game 2
PN vs. IH, JG

Game 3
PN vs. HO, JW

Please answer the following question:
Based on the results above, how strong do you think player PN is?

very weak very strong

Continue



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?

Games

Game 1
Kevin VS. Jason 

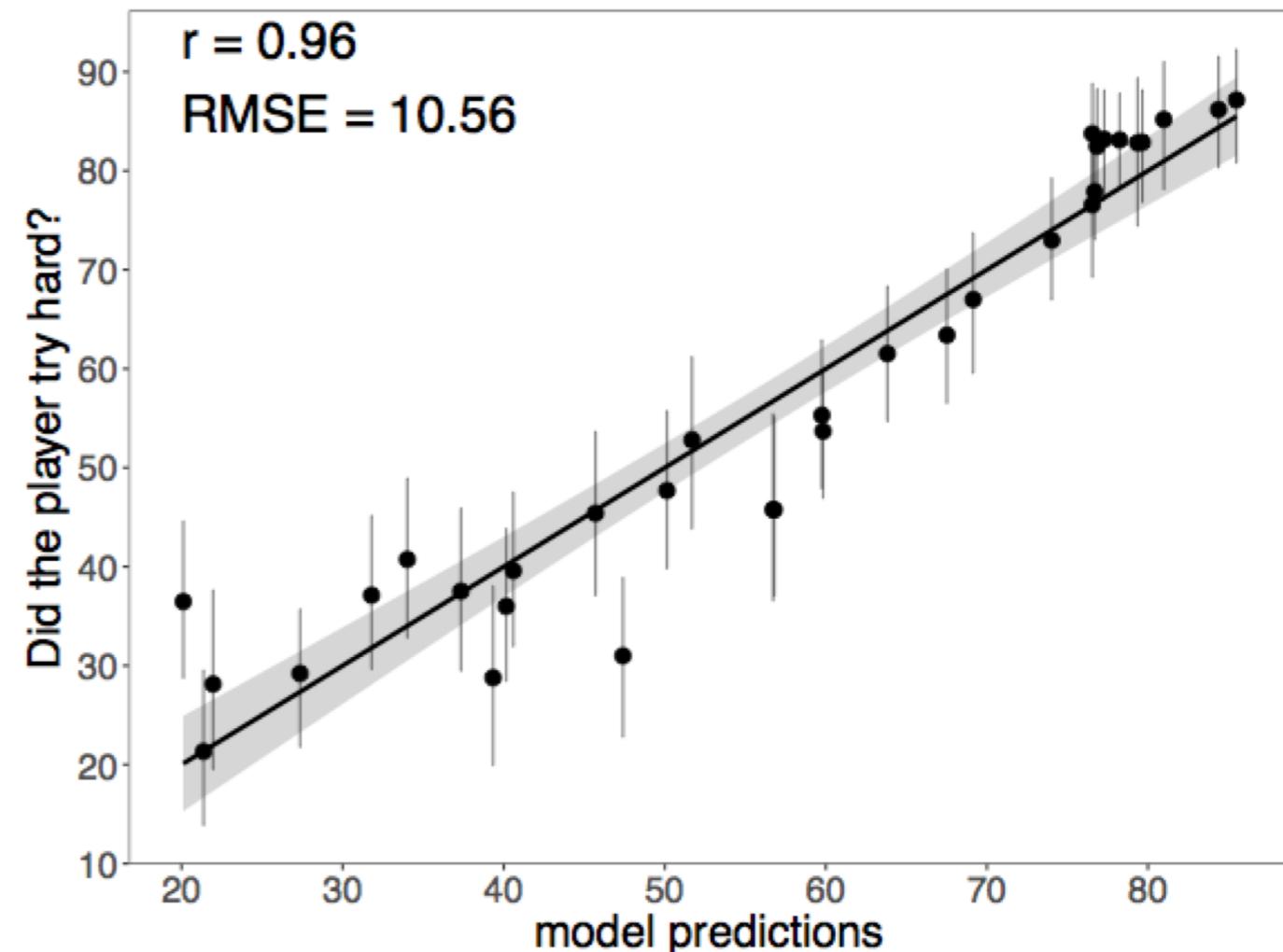
Game 2
 Kevin VS. Jason

Game 3
 Kevin VS. Jason

Please answer the following question:

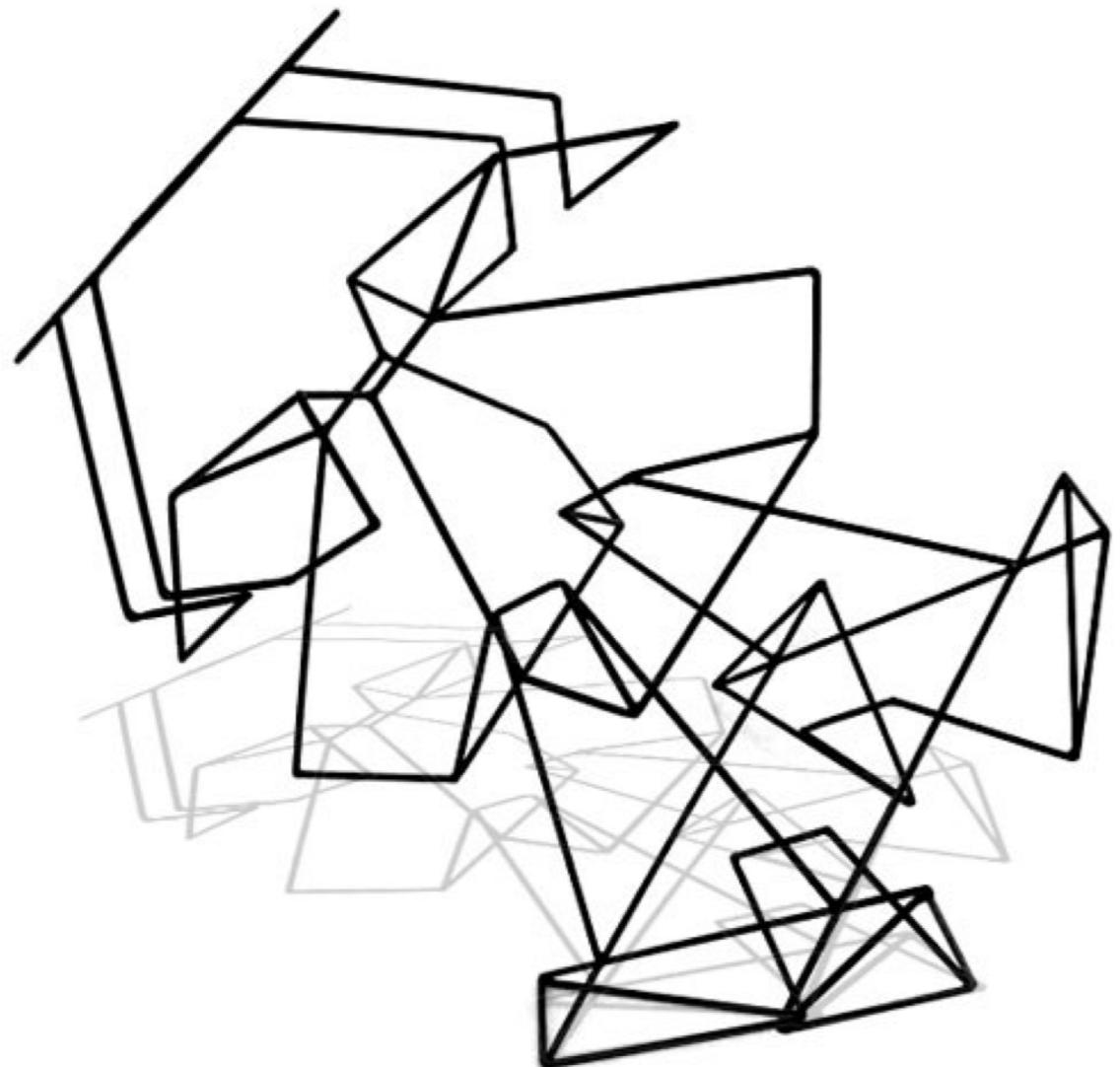
How likely is it that Jason tried hard in Game 1?

very unlikely very likely



Programs in the mind

Structure



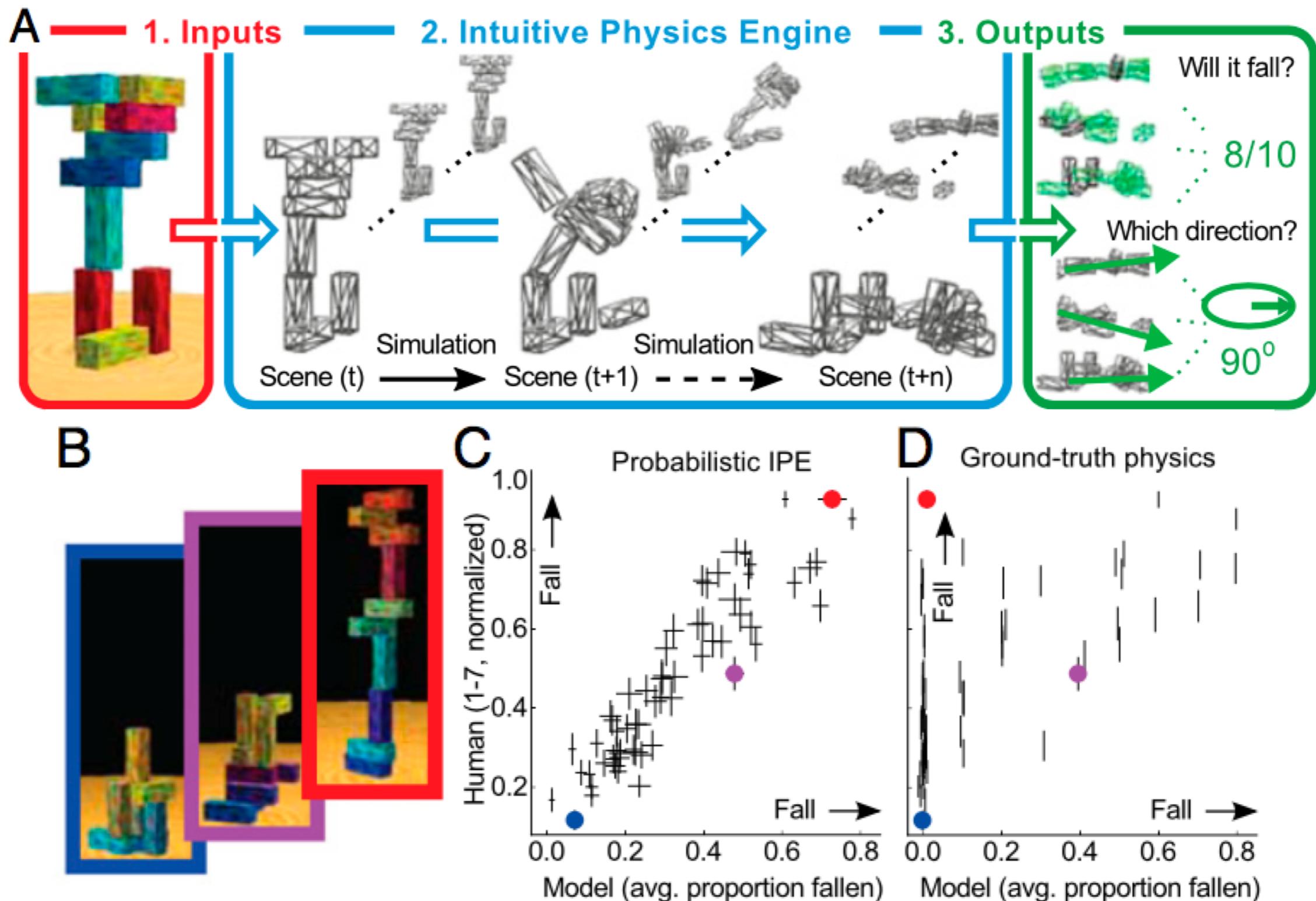
Probability



Knowledge

Uncertainty

Programs in the mind: causal models of a domain



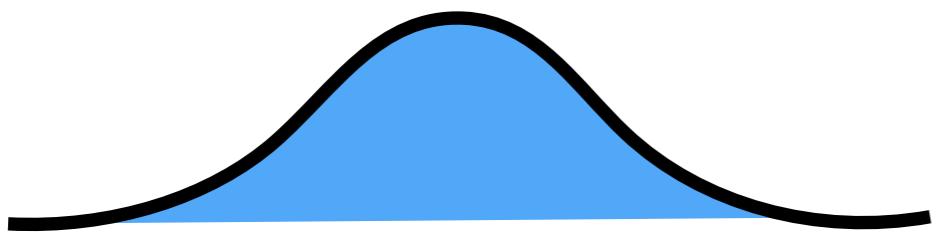
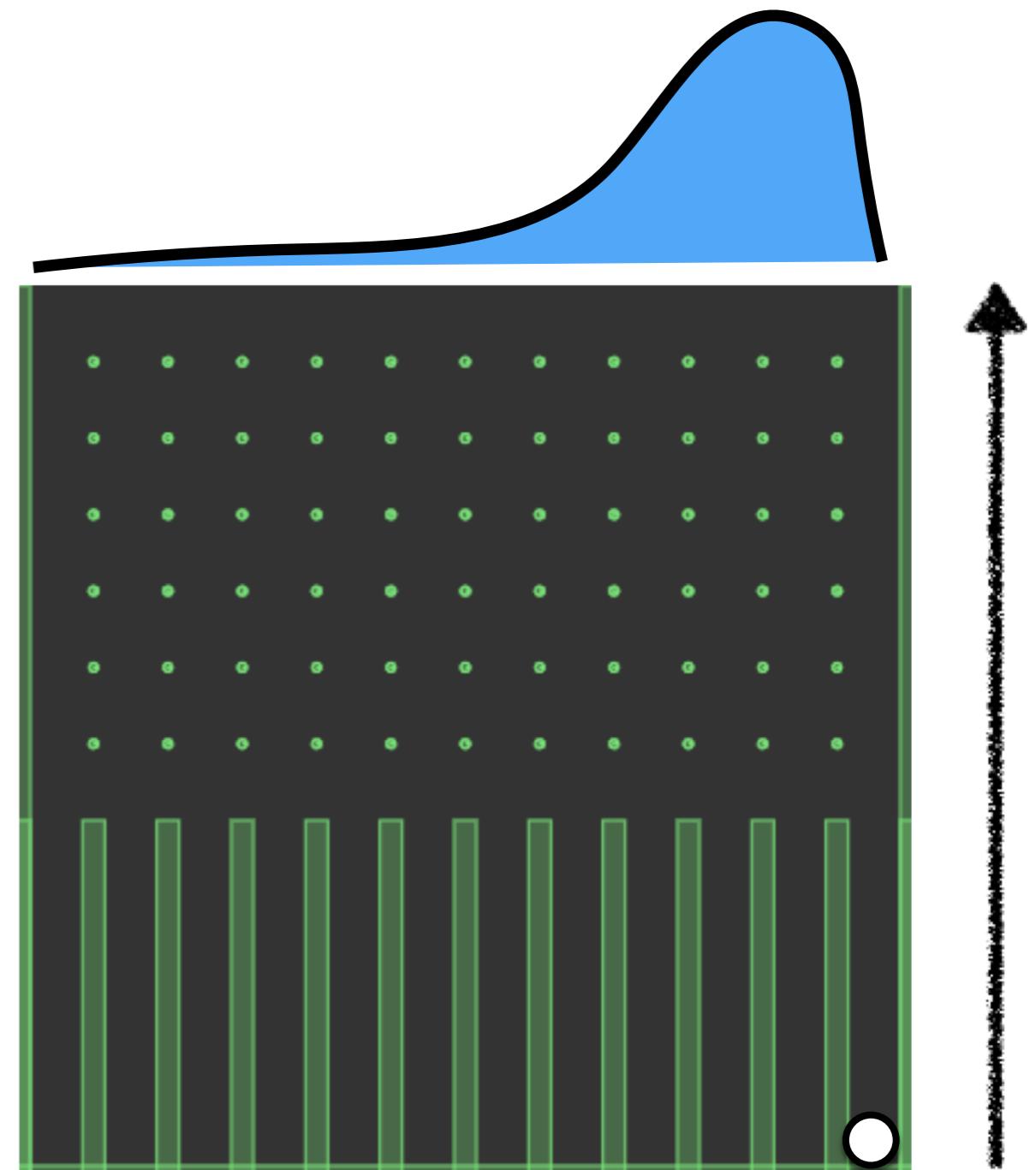
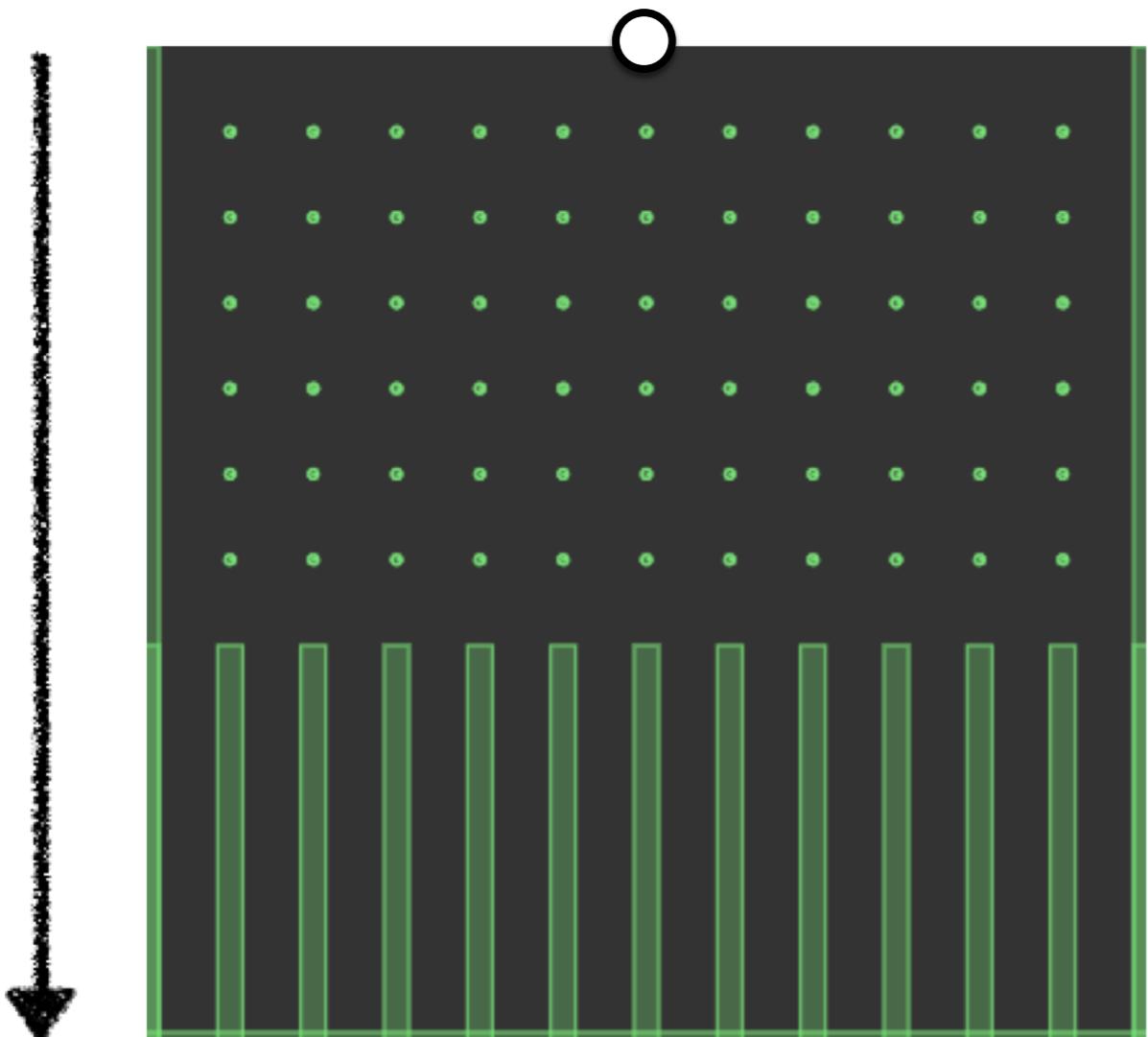
Battaglia, Hamrick, & Tenenbaum (2013) Simulation as an engine of physical scene understanding.

Proceedings of the National Academy of Sciences

Probabilistic inference

Run forward

Where will the ball land?



Reason backward
Where did the ball come from?

Why WebPPL?

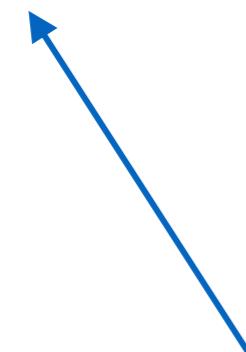
WebPPL

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)

Recent PPLs (Pyro, Gen) have a steeper learning curve, require more thought about inference, but keep the flexibility of WebPPL and work faster



Probabilistic programs

D
I
Y
OURSELF

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

http://bit.do/webppl_966

→ notes/1_webppl_basics.md

→ <http://webppl.org>

1. WebPPL basics

WebPPL basics

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

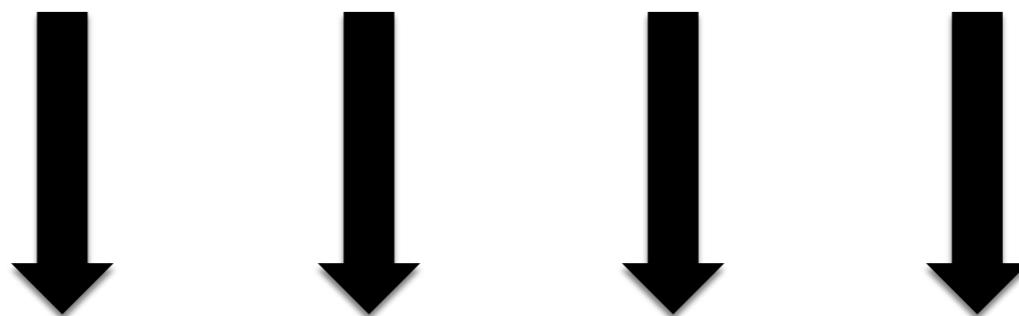
WebPPL basics

- The `map` function

```
var mySquare = function(x){return x*x}  
var someNumbers = [1,2,3,4]  
display(map(mySquare, someNumbers))
```

In:

[1, 2, 3, 4]



Out:

[1, 4, 9, 16]

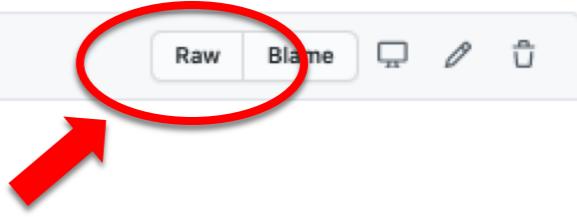
WebPPL basics

- 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)

Practice time!

1. Create several more objects like the kevin and josh objects from above for some of your fellow students. Assign them several properties, including strength.
2. Create a function showStrength() for displaying the strength of a student.
3. Map the function showStrength() to an array of students and instructors.
4. Amend the returnWinner() function to handle ties.

210 lines (163 sloc) | 5.04 KB

Raw Blame 

WebPPL basics

- Test the different code snippets by navigating here: webppl.org
- You can open a new file and save any code you've written.
- Check out [appendix-js-basics](#) for other Javascript basics, including mathematical and logical operations.

Click here for answers!

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

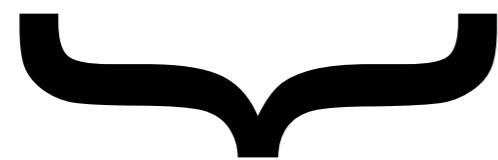
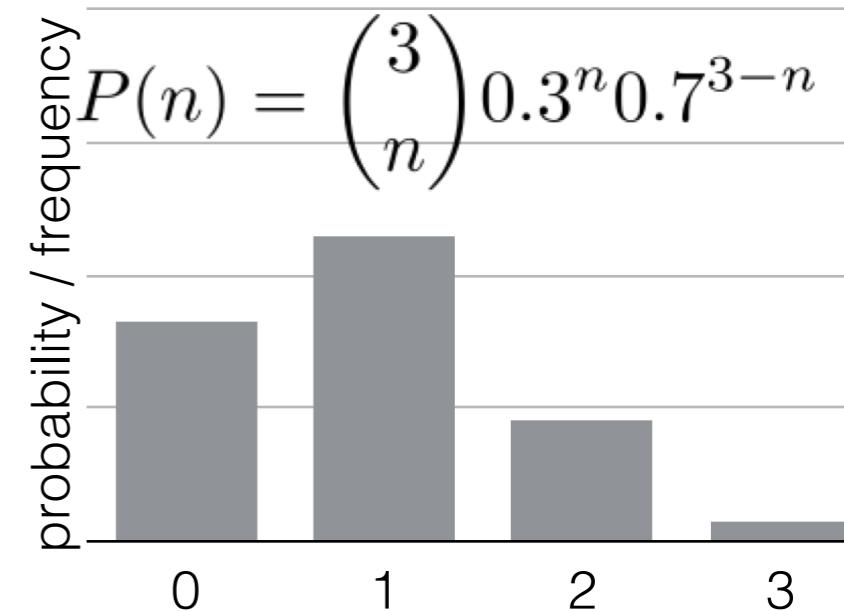
Building generative models

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



Sampling



Distributions

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

Goodman, Mansinghka, Roy, Bonawitz, & Tenenbaum (2008) Church: A language for generative models.

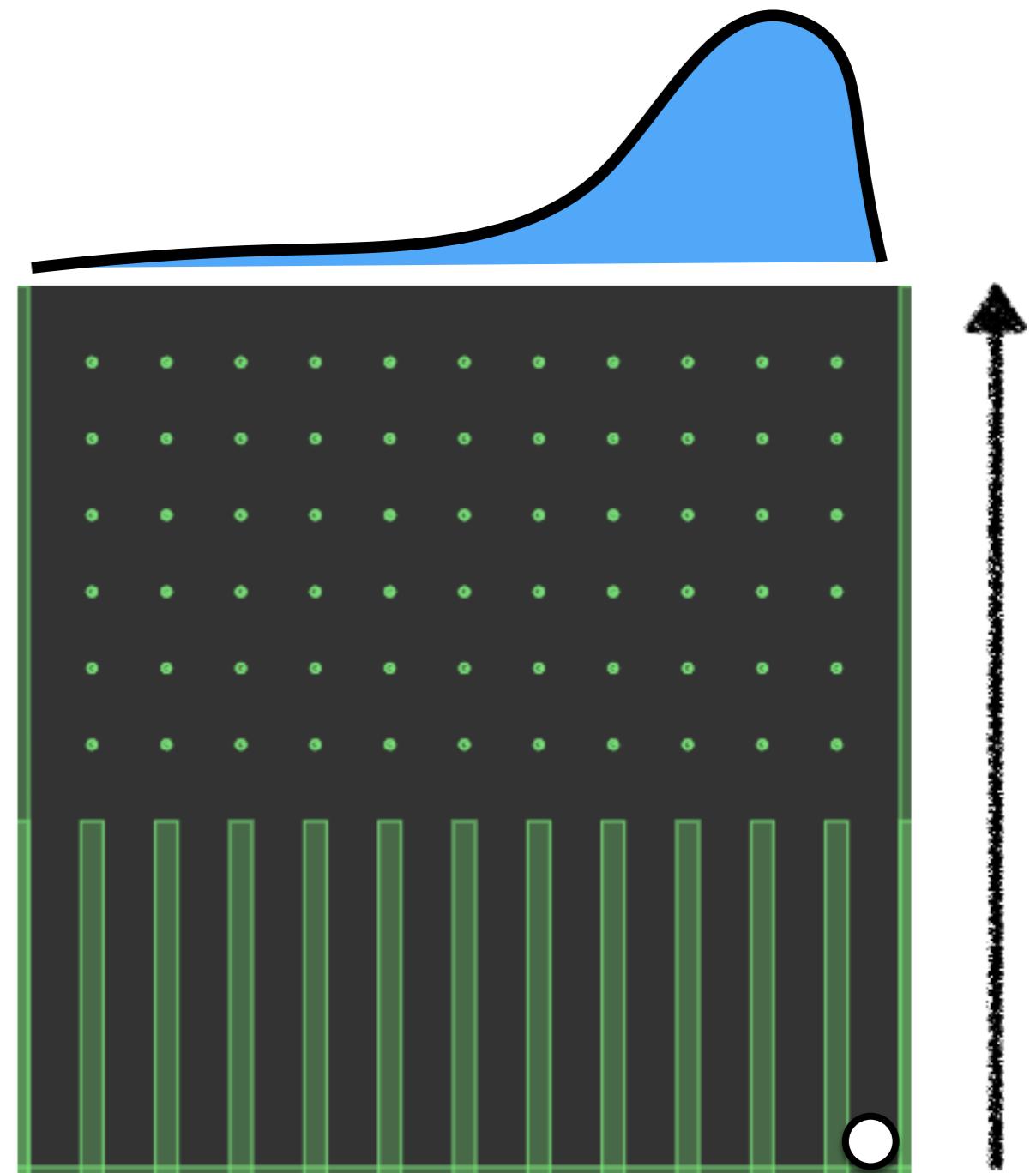
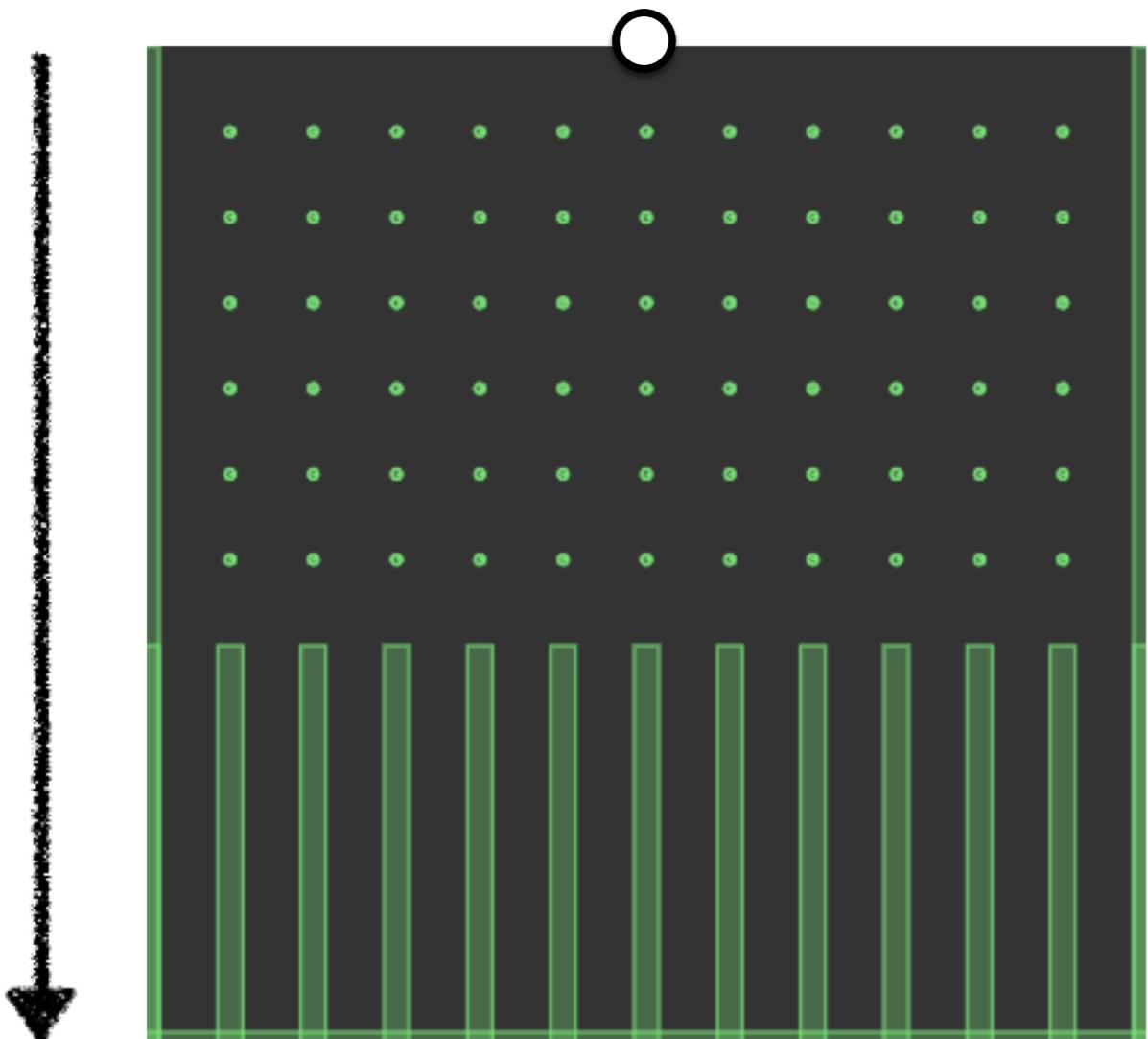
Uncertainty in Artificial Intelligence

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)
```

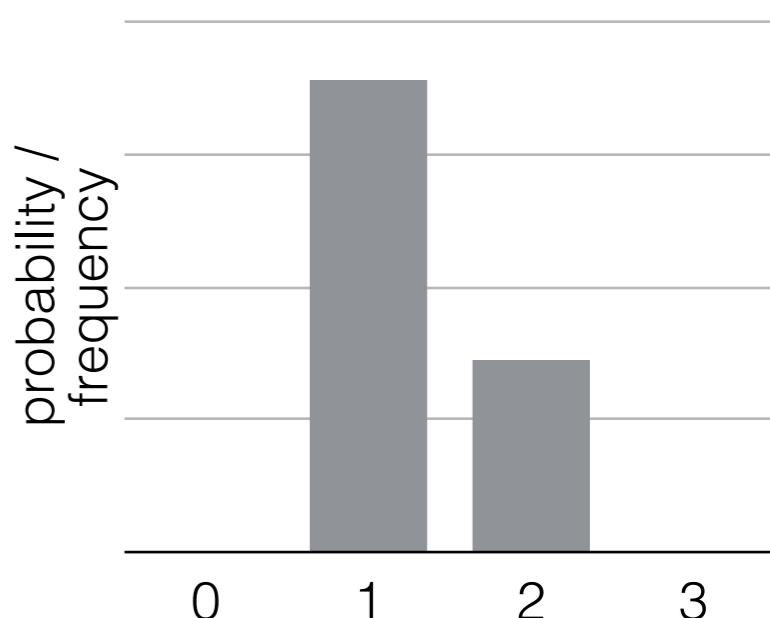
```
    var b = flip(0.3)
```

```
    var c = flip(0.3)
```

```
    condition(a + b == 1)
    return a + b + c}
```

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

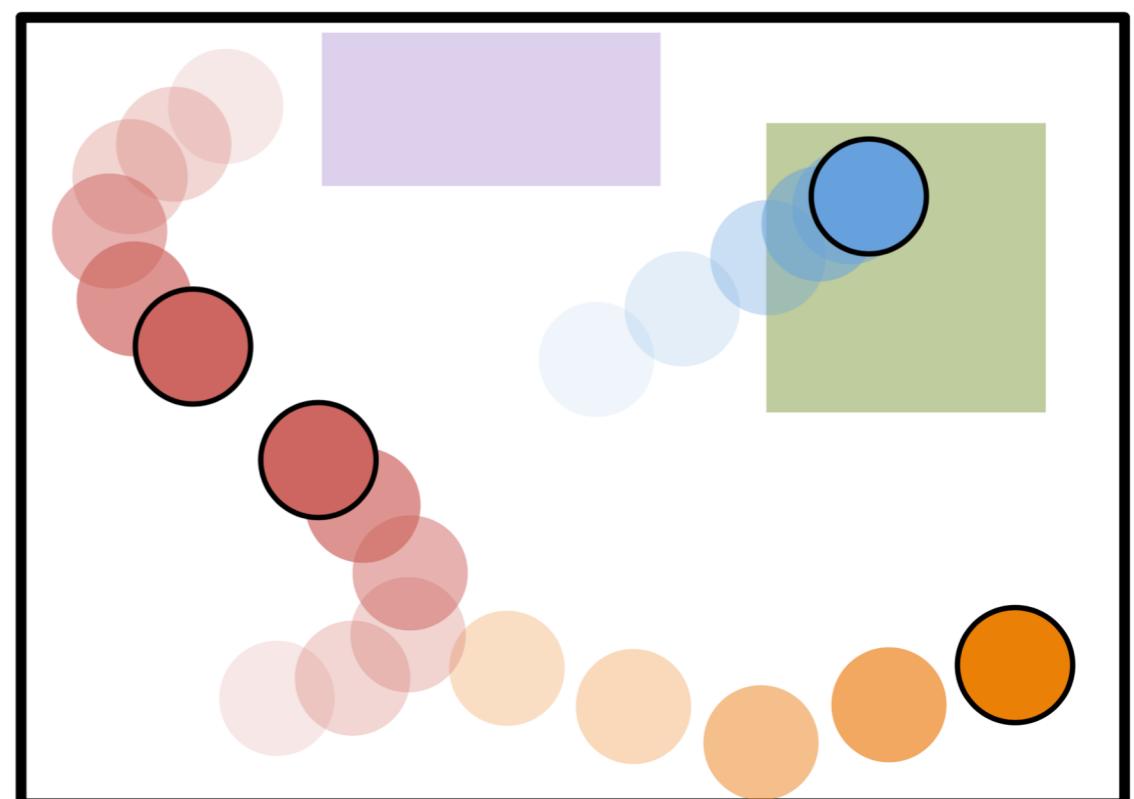
"Concepts have a language-like **compositionality** and encode probabilistic knowledge. These features allow them to be extended **productively** to new situations and support flexible reasoning and learning by **probabilistic inference.**"

```
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

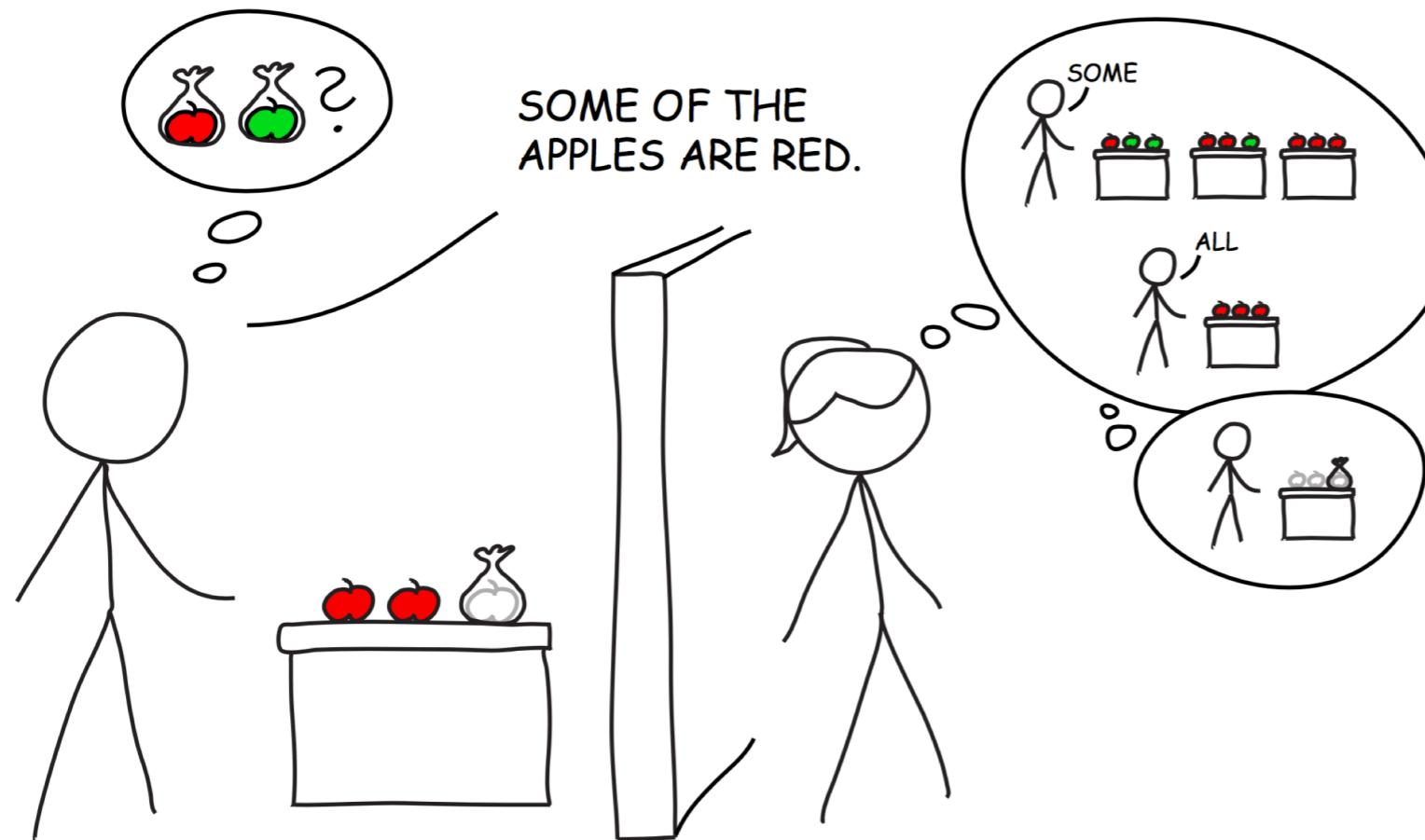
	(i)	(ii)	(iii)
Level N			
Innate concepts			
Level 2			
Entity types	<i>Entity</i>	<pre>(define (make-entity property1 property2 ...) (list property1 property2 ...))</pre>	
	<i>Newtonian Dynamics</i>	<pre>(define (run-dynamics entities forces init-cond steps dt) (if (= steps 0) '() (let* ((m (get-mass 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>	
Properties	<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>	
	<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>	②
	<i>Global:</i> ○ →	<pre>(define (global-force) (let* ((d (uniform-draw compass-dir))) (lambda (o) (* k d))))</pre>	
Level 1			
Property values	<ul style="list-style-type: none"> ● : large mass ○ : medium mass ■ : small mass ■ : high friction ■ : no friction 	<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>	
Level 0 (data)	<i>Initial conditions</i>	<pre>(define scenario (let* ((init-cond (sample-init world-entities)) (run-dynamics world-entities world-forces init-cond steps dt))) (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 (2018) Learning physical parameters from dynamic scenes. Cognitive Psychology

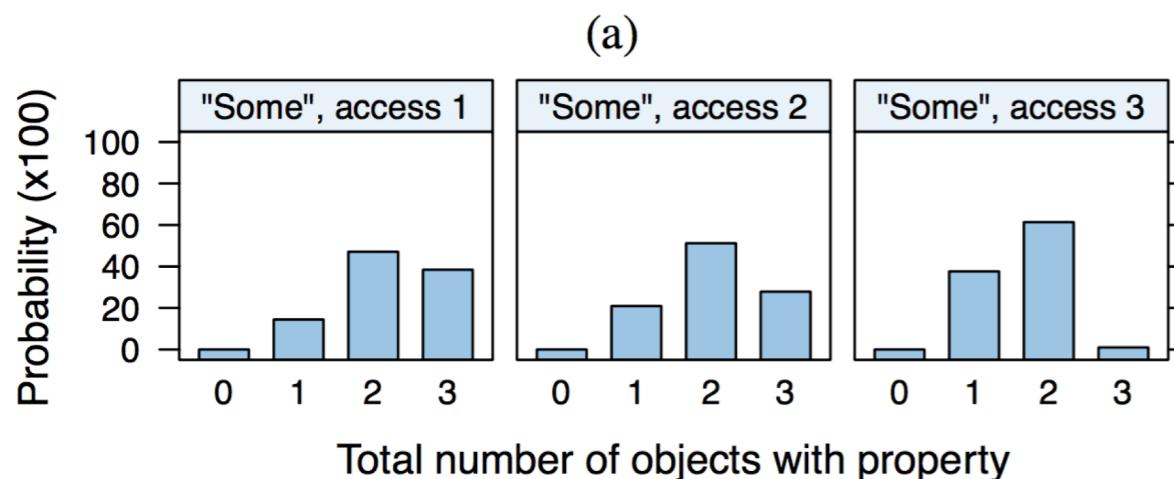
Some more cool examples: Pragmatic inference



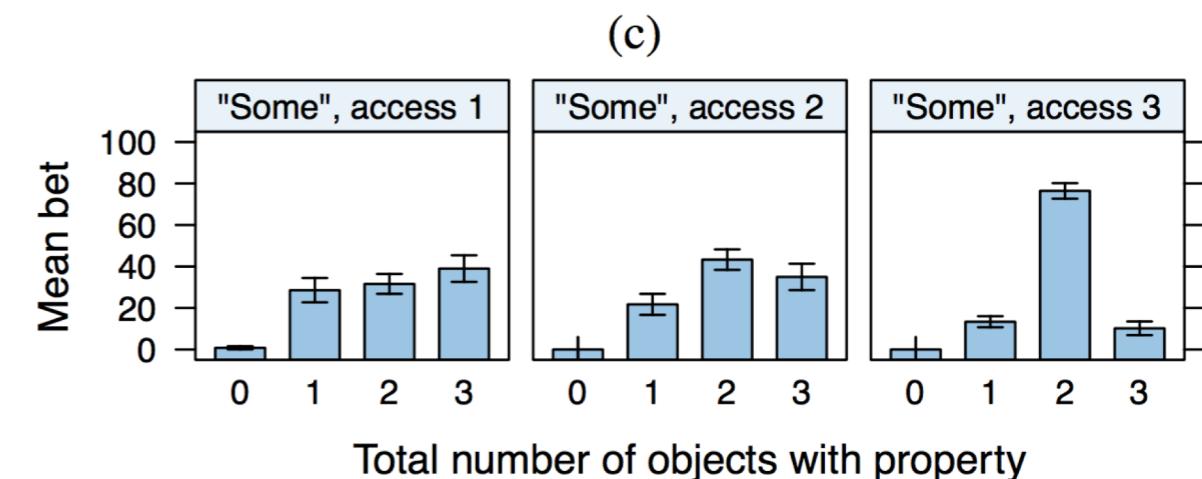
Scalar implicature

("some" but not "all")

Model



Experiment



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
- 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](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>
- 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 !