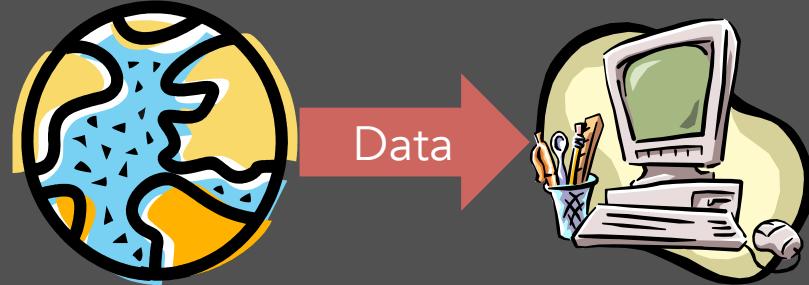


# CSE 512 - Data Visualization Uncertainty



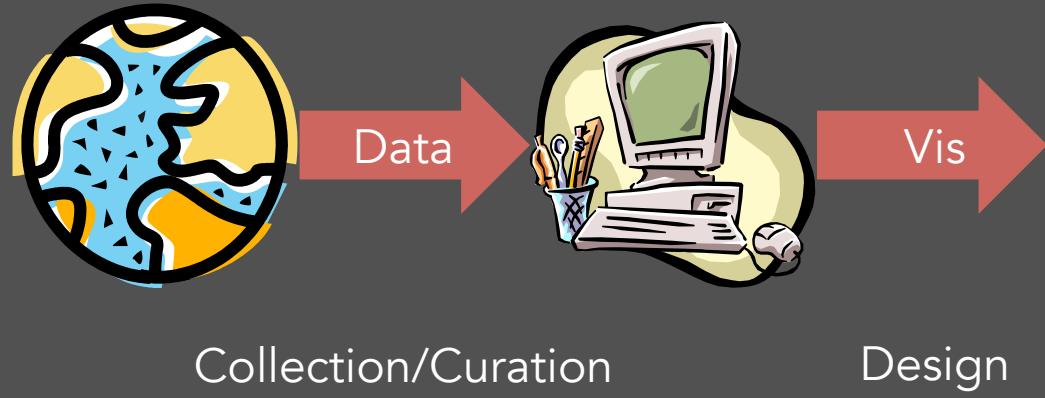
Michael Correll University of Washington

# The Visualization Pipeline

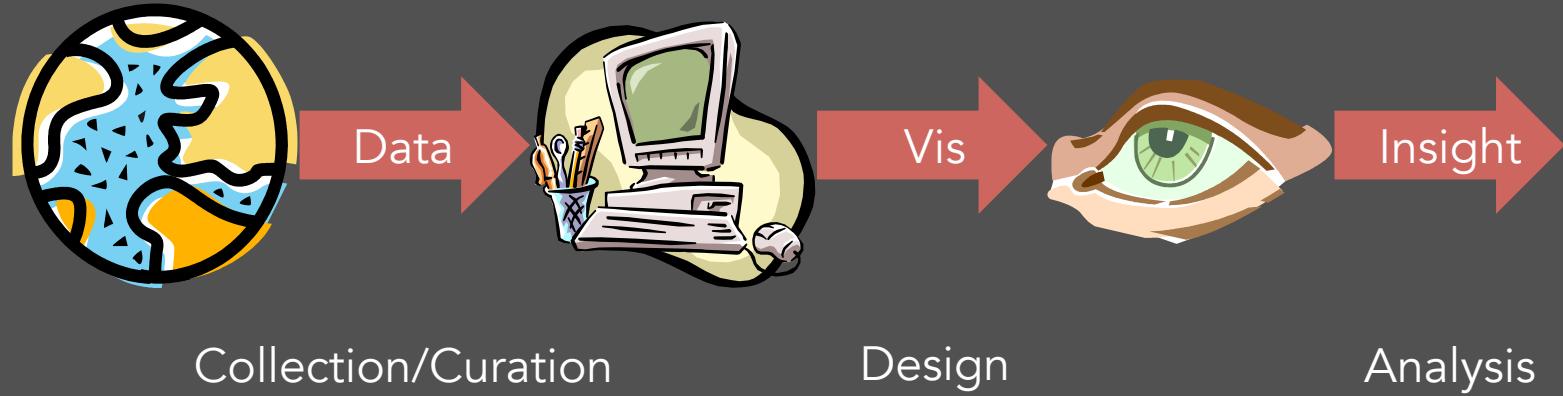


Collection/Curation

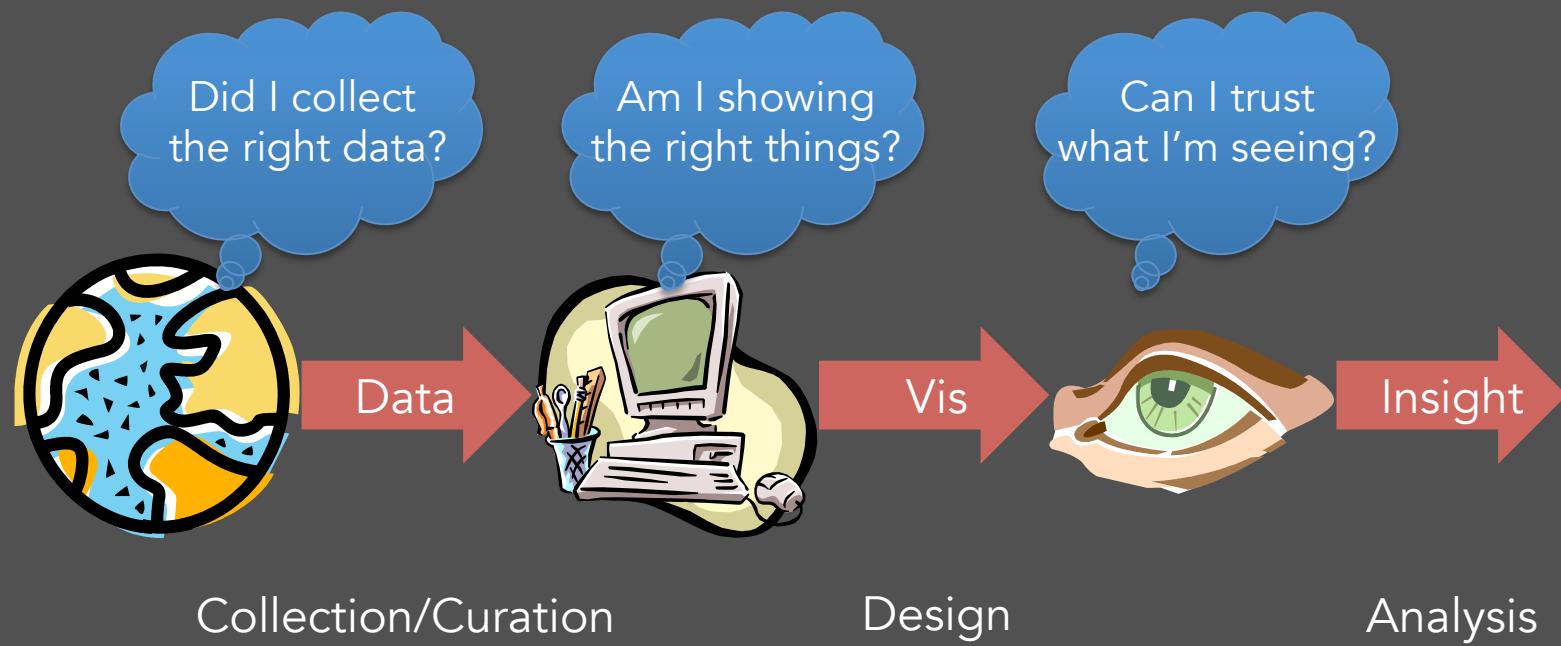
# The Visualization Pipeline



# The Visualization Pipeline



# The Visualization Pipeline?



# Unknown Unknowns



# Things “Uncertainty” Can Mean

Doubt

Risk

Variability

Error

Lack of Knowledge

Hedging

...

# Uncertainty Visualization

There are different **types** and **sources** of uncertainty.

We can **quantify** or **model** our uncertainty.

The visual presentation of uncertainty can **clash** with cognitive and perceptual biases.

# Terminology

# Terminology

Aleatory Uncertainty

Epistemic Uncertainty

Type I error

Type II error

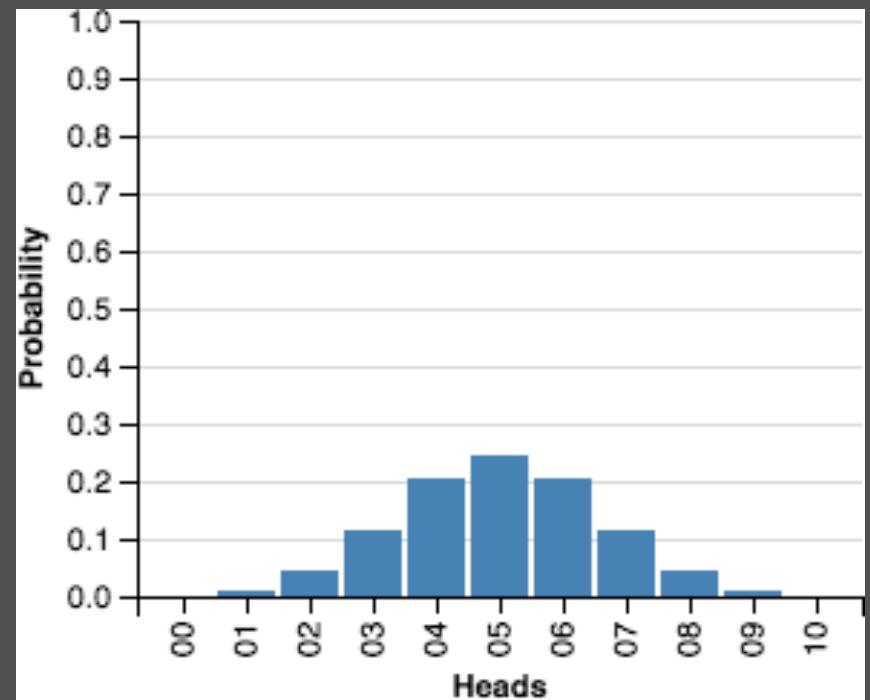
Precision

Bias

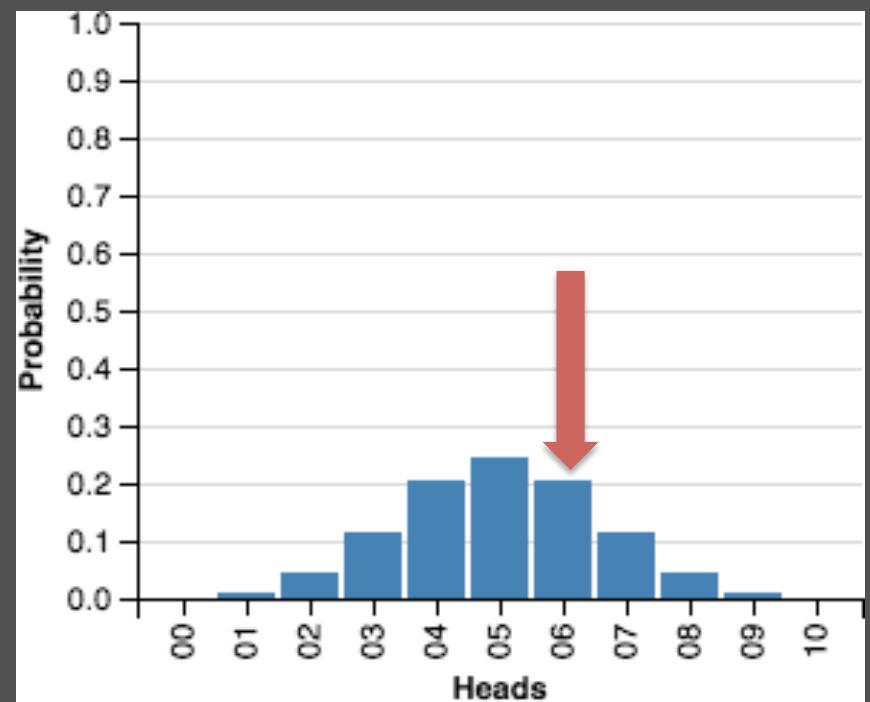
# Aleatory Uncertainty



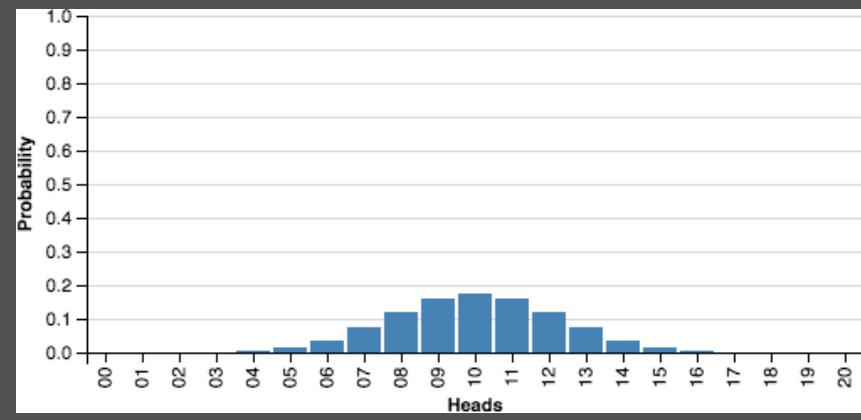
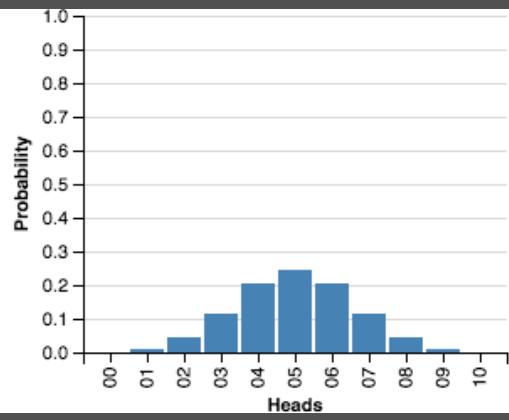
# Aleatory Uncertainty



# Aleatory Uncertainty

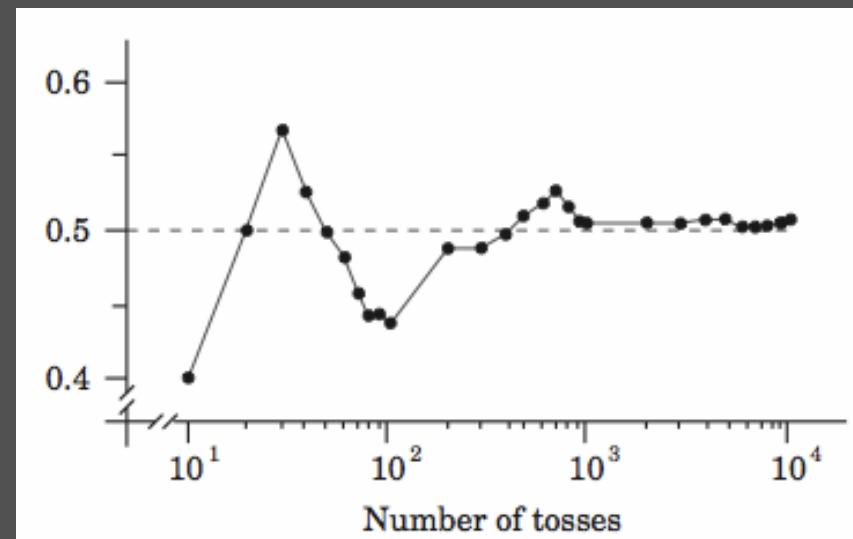


# Aleatory Uncertainty



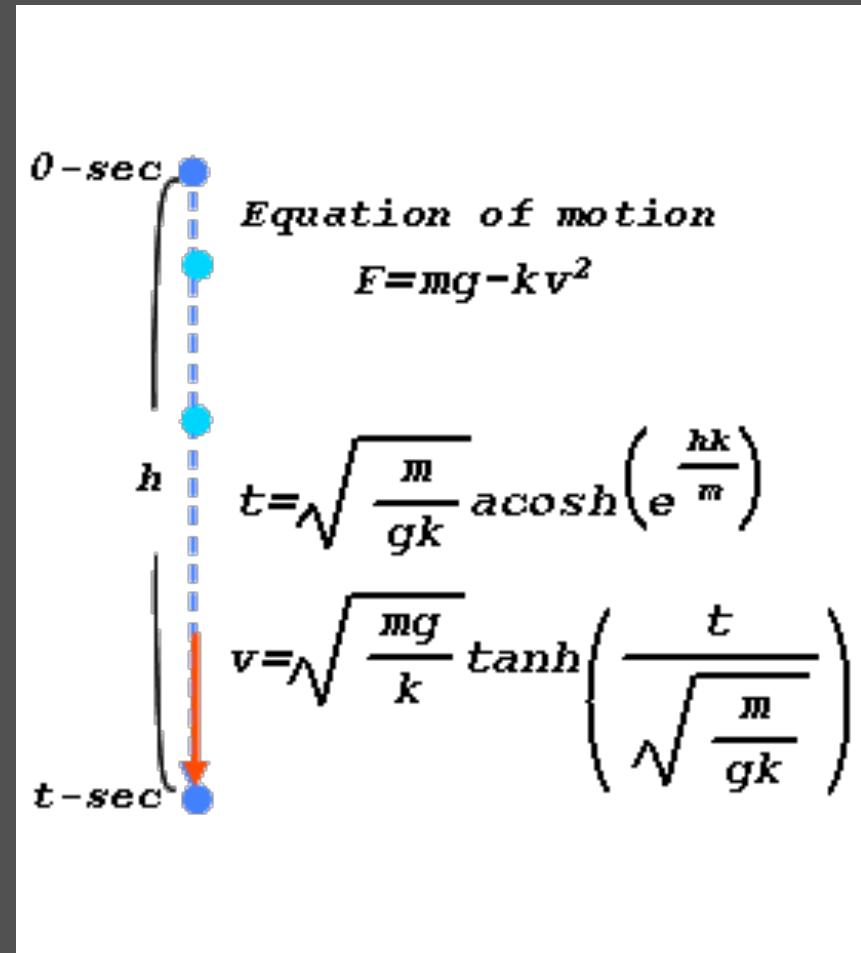
# John Edmund Kerrich





**FIGURE 4.1.1** Proportion of heads versus number of tosses for John Kerrich's coin-tossing experiment.

# Epistemic Uncertainty



# Uncertainty Types

## Aleatory

Variability: things that we don't know (but can reason about the likelihood of).

## Epistemic

Things we could in principle know for certain, but have not measured.

# Should I Bring an Umbrella?



# Decision Uncertainty

“50% Chance of Rain”



# Risk and Error



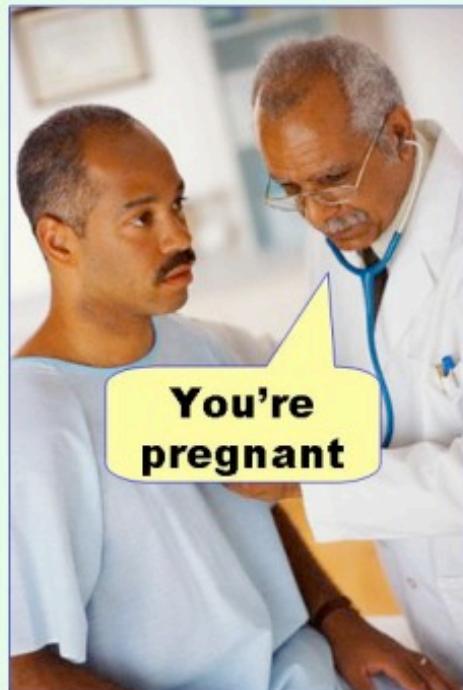
||

-

# Type I and Type II

## Type I error

(false positive)



## Type II error

(false negative)

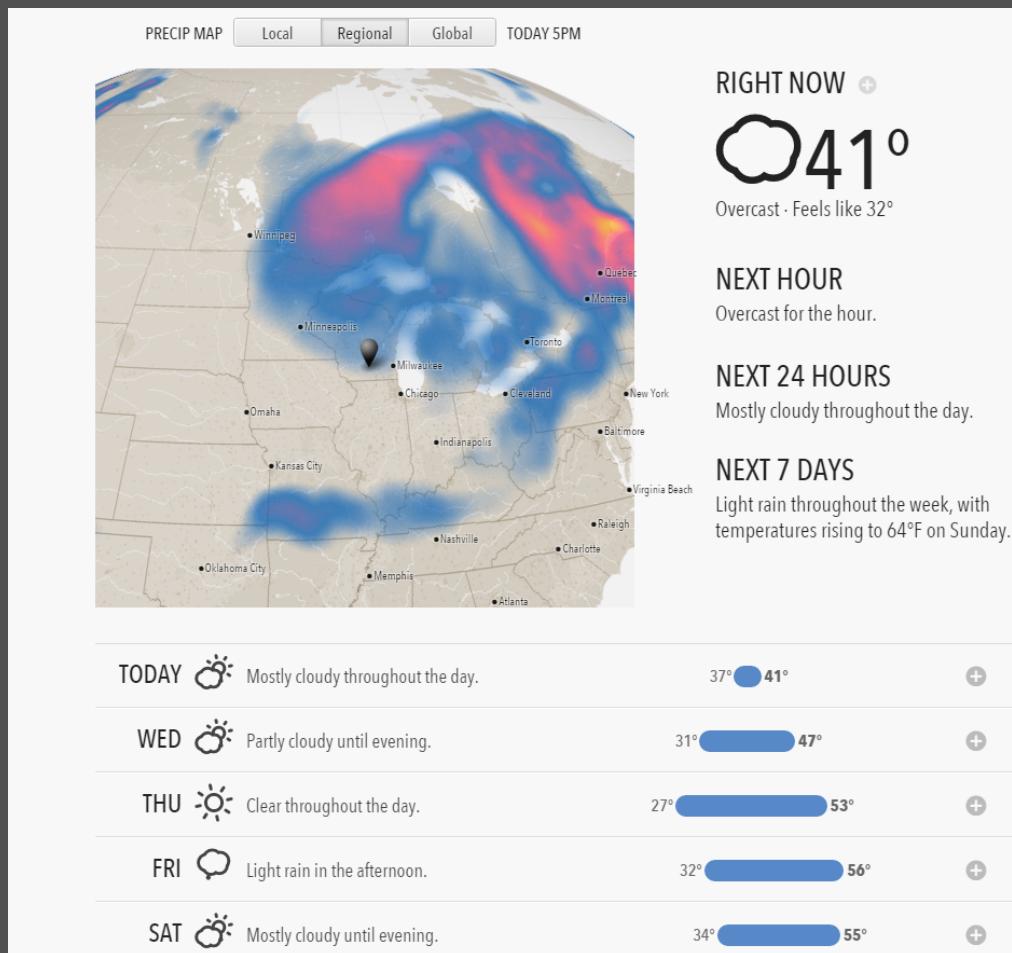


# Model Uncertainty

“50% Chance of Rain”



# Model Uncertainty



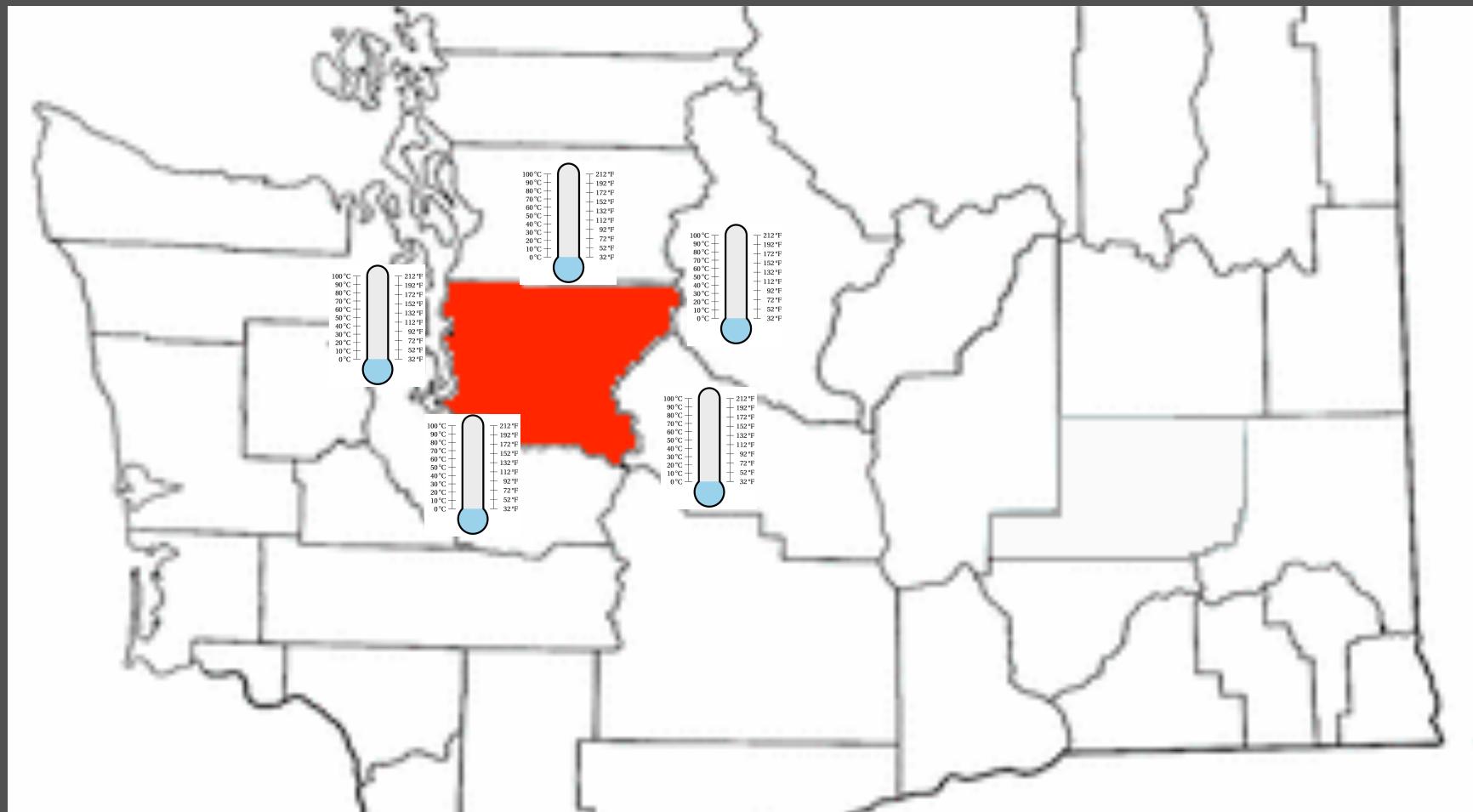
# Model Uncertainty



# Measurement Uncertainty



# Measurement Uncertainty



# Measurement Uncertainty

**Accuracy**



# Measurement Uncertainty

**Accuracy**



# Measurement Uncertainty

**Accuracy**



**Precision**



# Measurement Uncertainty

**Accuracy**



**Precision**

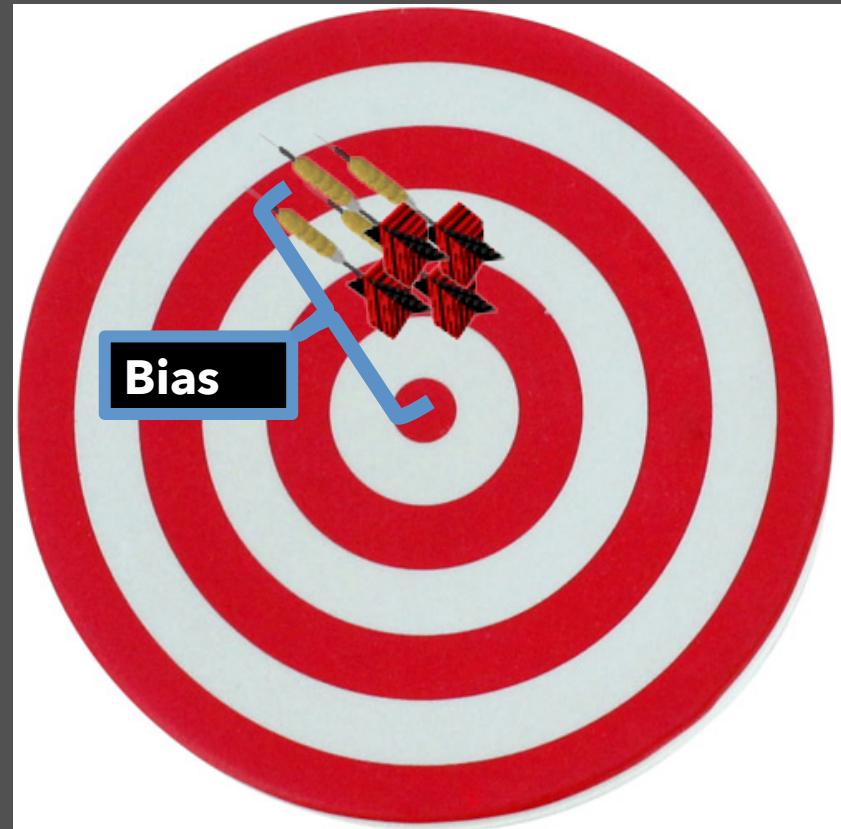


# Measurement Uncertainty

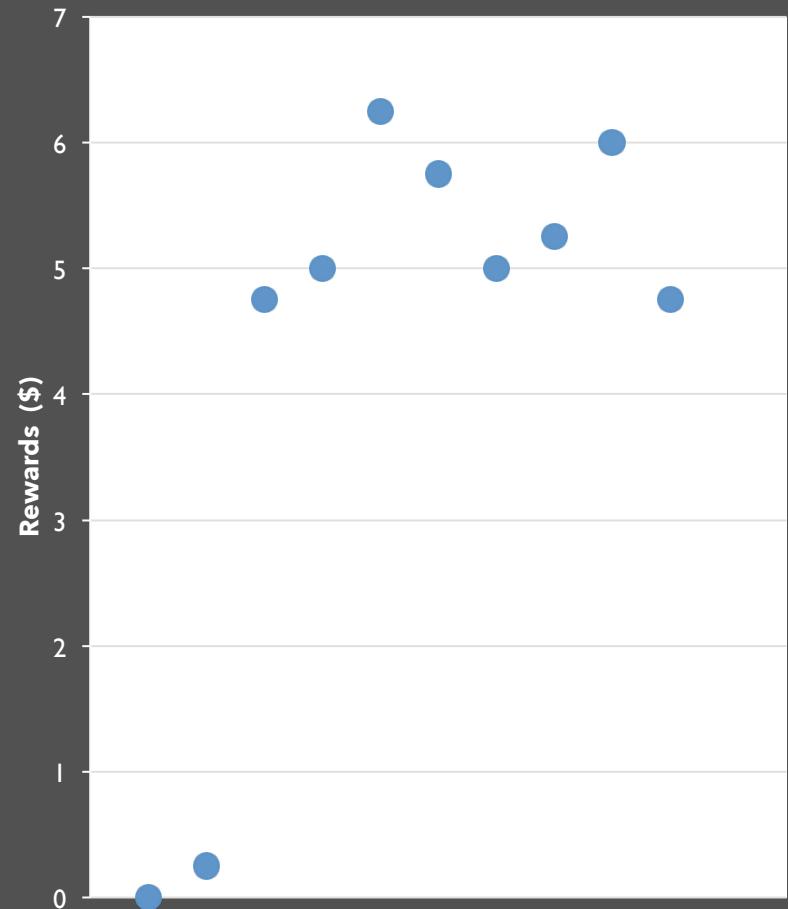
**Accuracy**



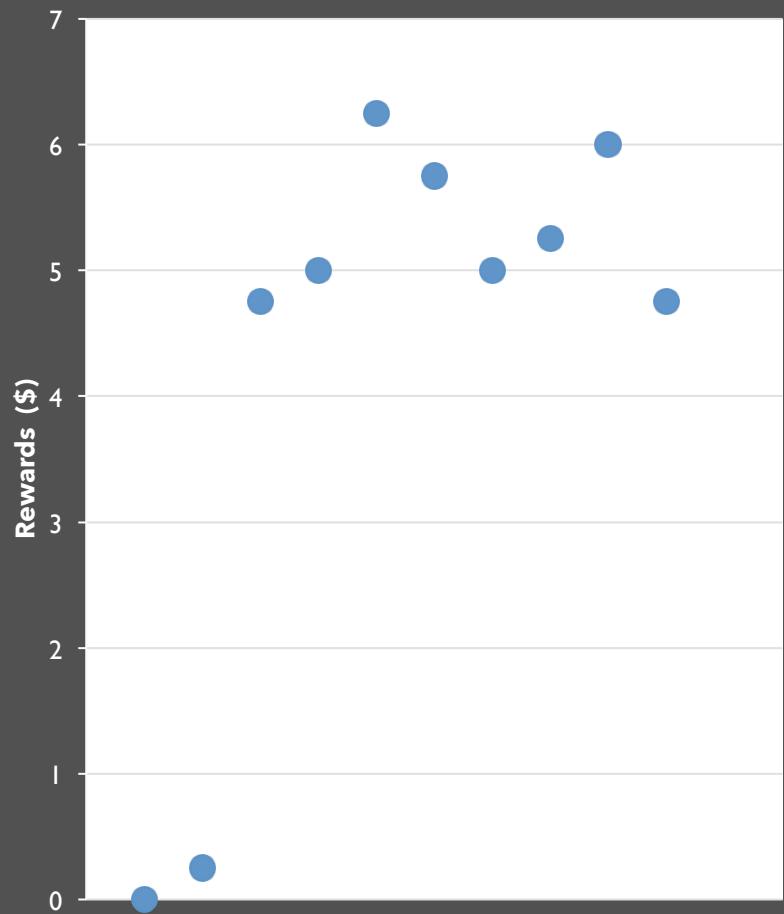
**Precision**



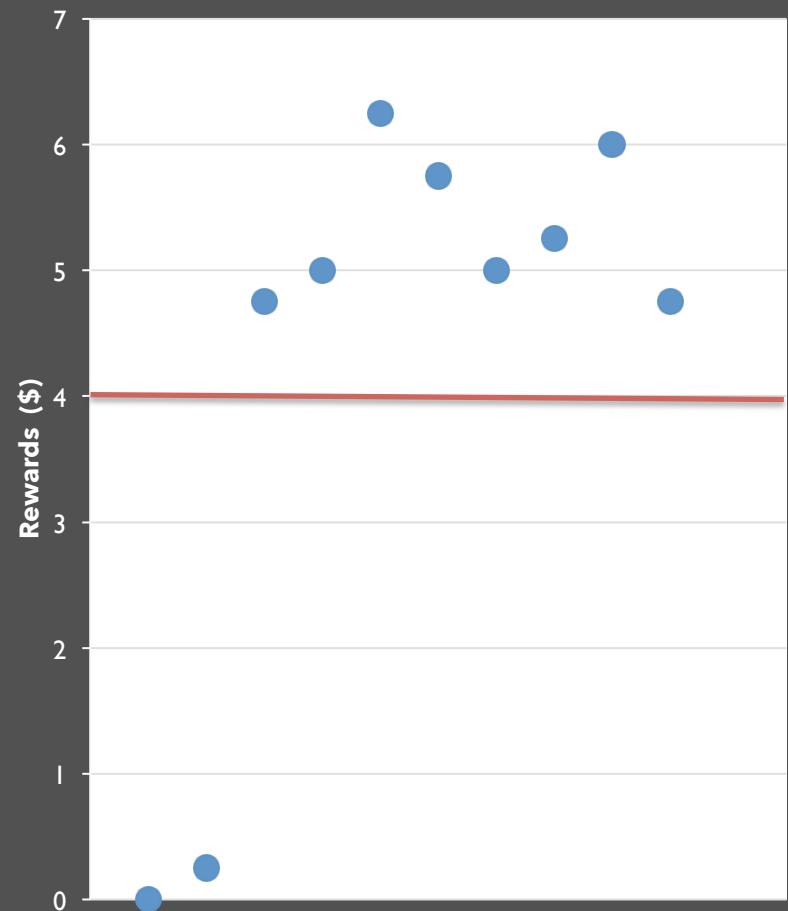
# Should you take this \$4 bet?



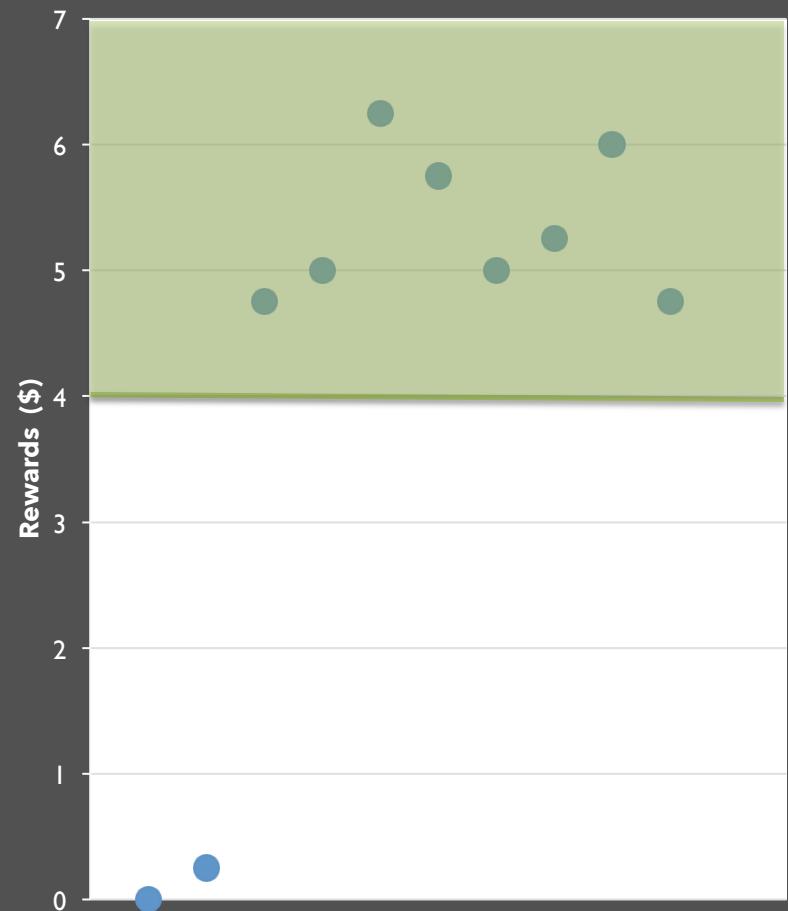
# Samples



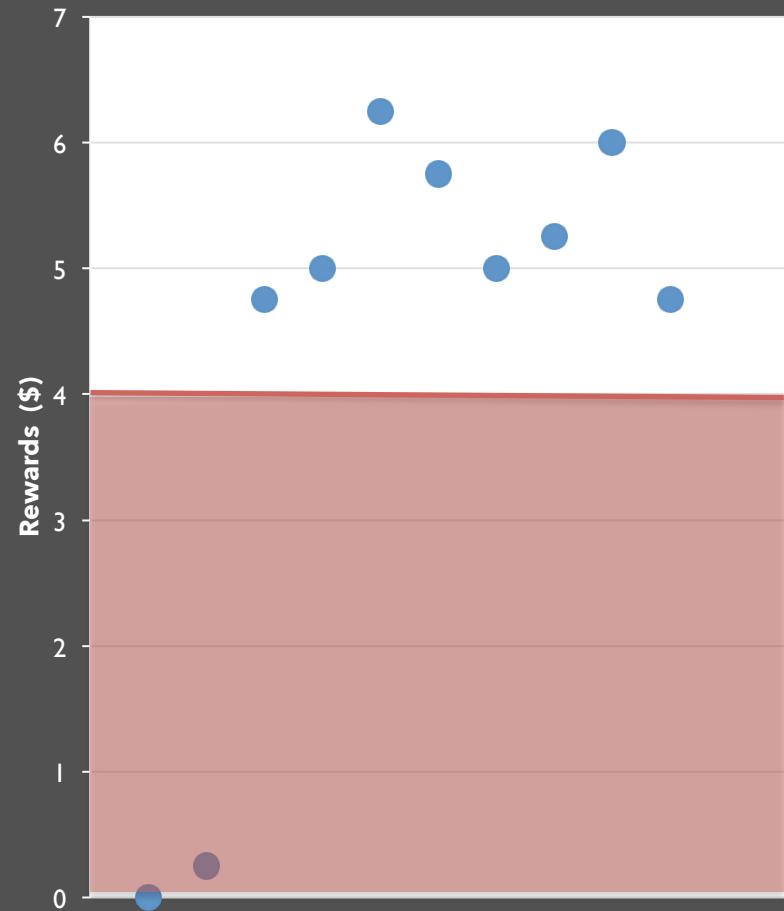
# Should you take this \$4 bet?



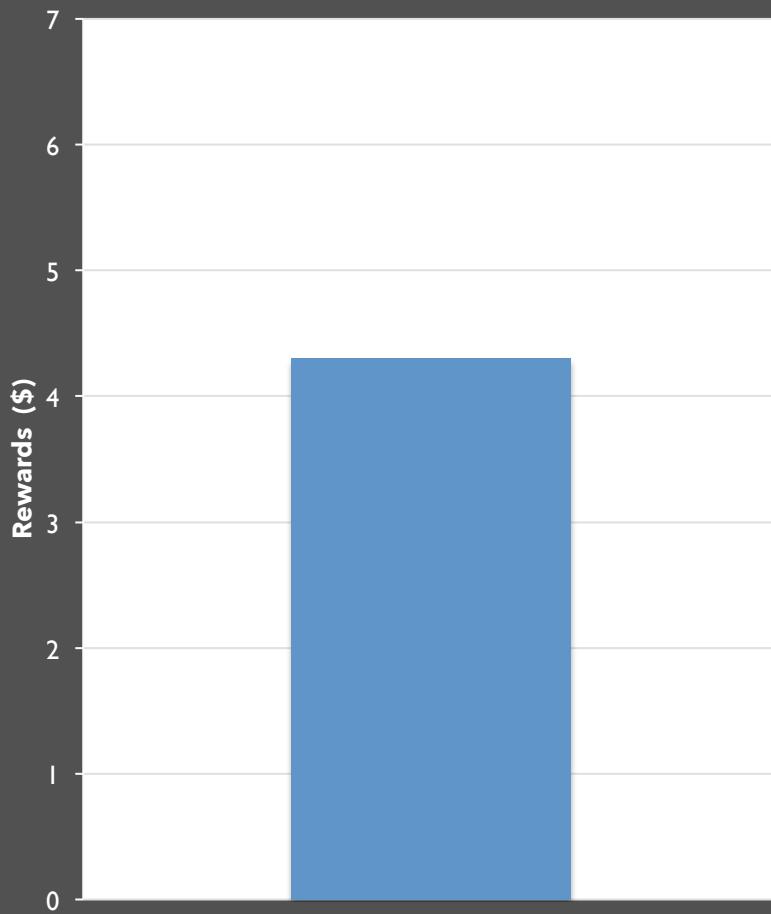
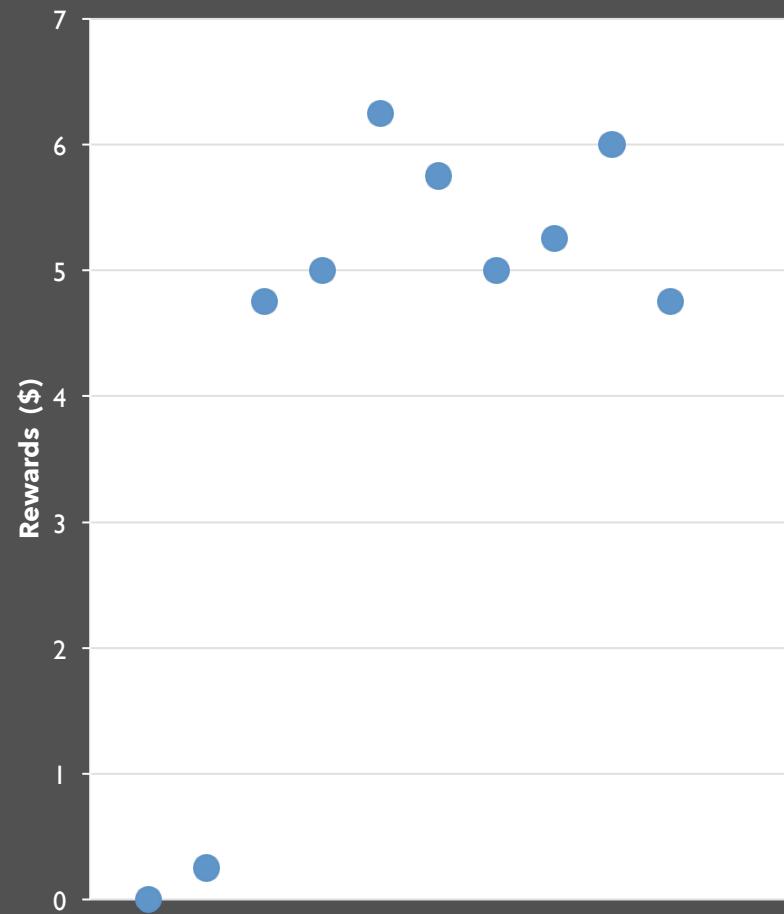
# Should you take this \$4 bet?



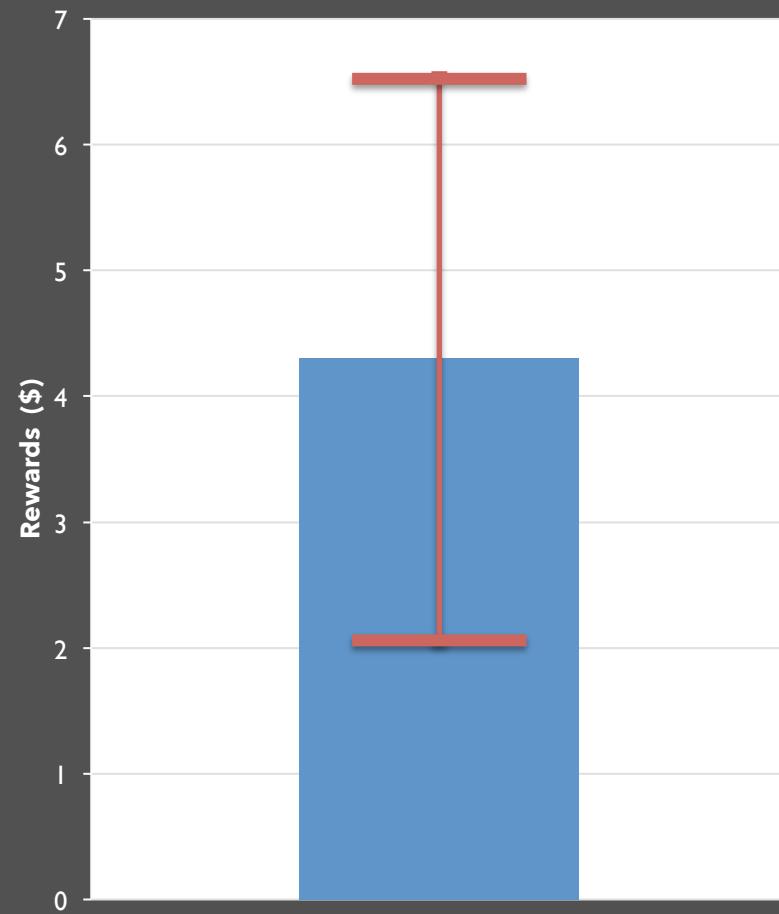
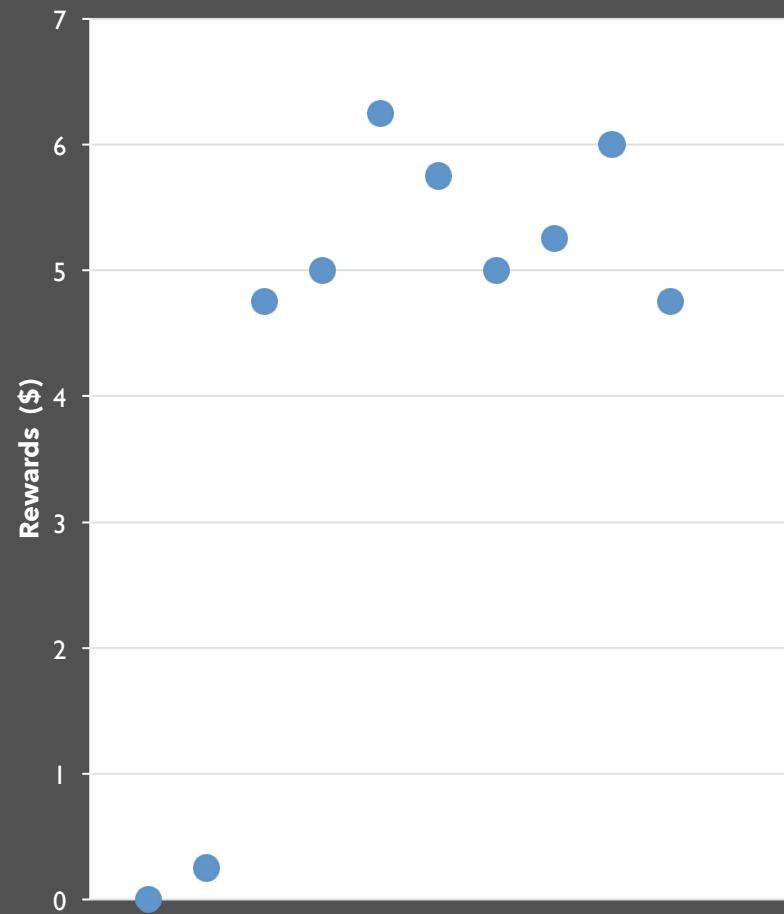
# Should you take this \$4 bet?



# Expected Value



# Mean And Error



# Statistical Inference

Assuming bet returns  
are normally  
distributed.

$M = 4.14$

$SD = 2.33$

$n = 10$

$P(\mu > 4) = \mathbf{0.95}$

■ Take the bet

# Statistical Inference

Assuming bet returns  
are normally  
distributed.

} MODEL

$M = 4.14$

$SD = 2.33$

$n = 10$

$P(\mu > 4) = \mathbf{0.95}$

| Take the bet

# Statistical Inference

Assuming bet returns  
are normally  
distributed.

$M = 4.14$

$SD = 2.33$

$n = 10$

$P(\mu > 4) = \mathbf{0.95}$

▀ Take the bet

} MODEL

} MEASUREMENT

# Statistical Inference

Assuming bet returns  
are normally  
distributed.

$$M = 4.14$$

$$SD = 2.33$$

$$n = 10$$

$$P(\mu > 4) = \mathbf{0.95}$$

Take the bet

} MODEL

} MEASUREMENT

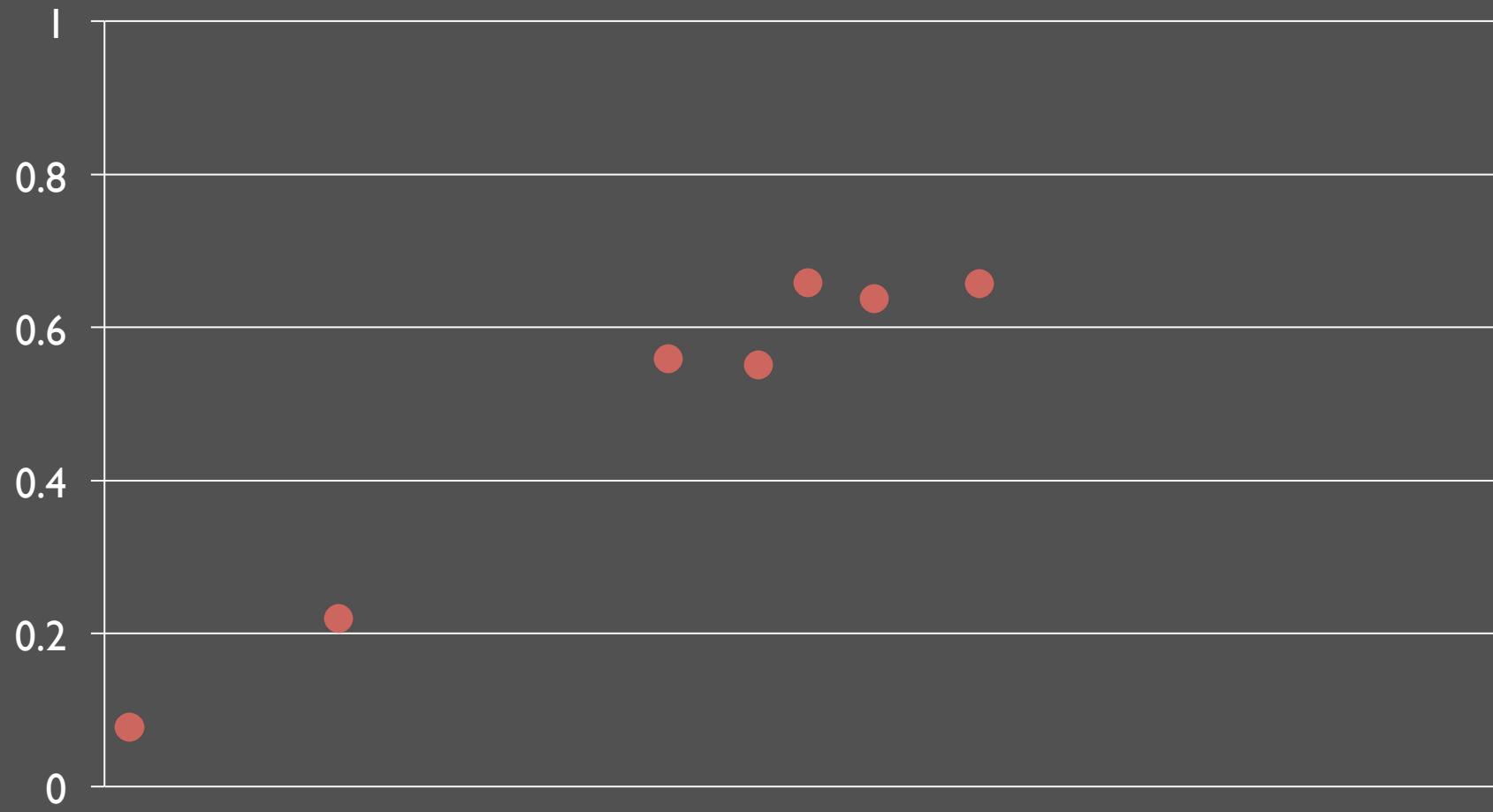
← DECISION

# Uncertainty Sources

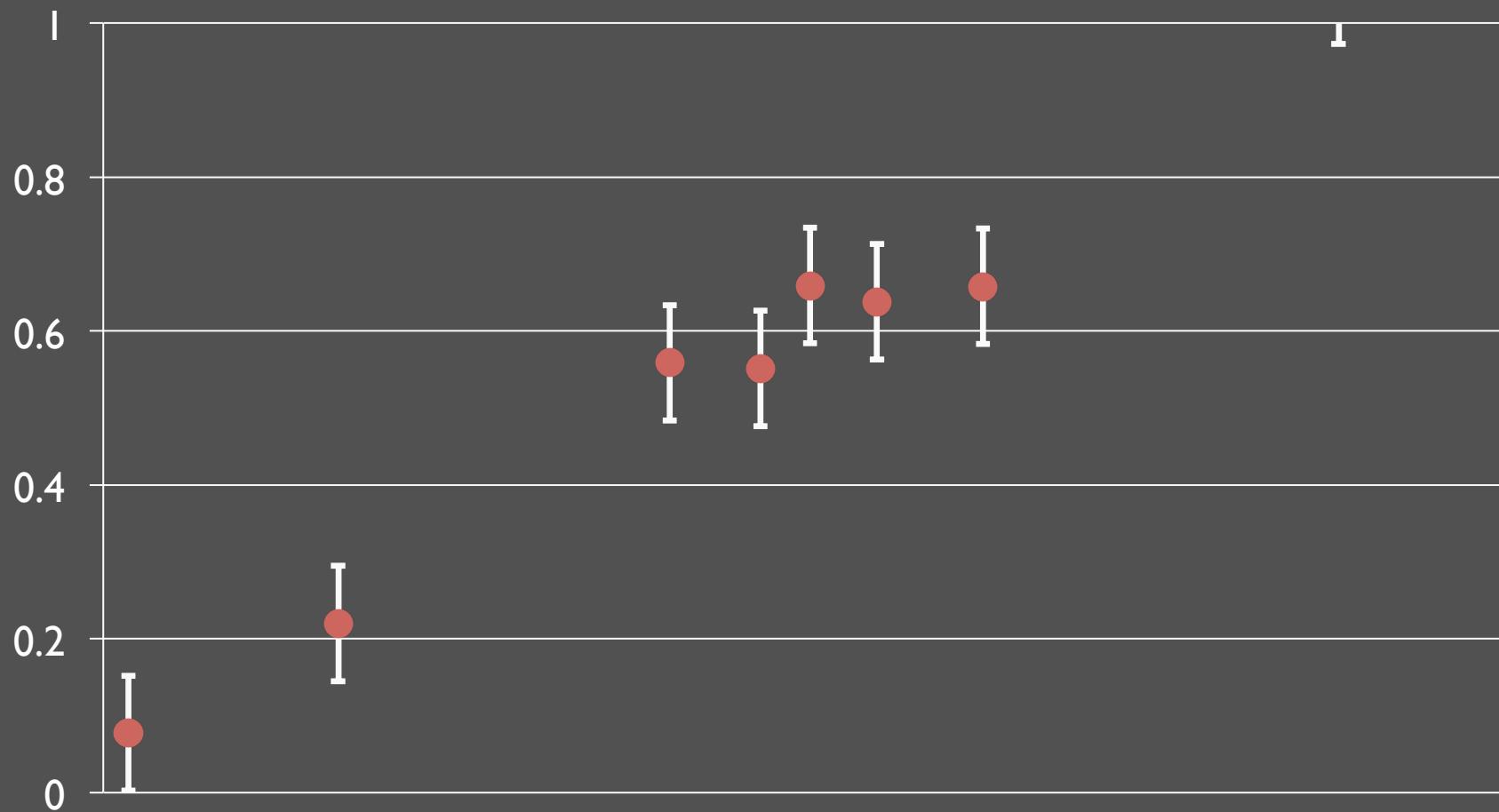
**Measurement Uncertainty:** "We're not sure what the data are"

**Model Uncertainty:** "We're not sure how the data fit together"

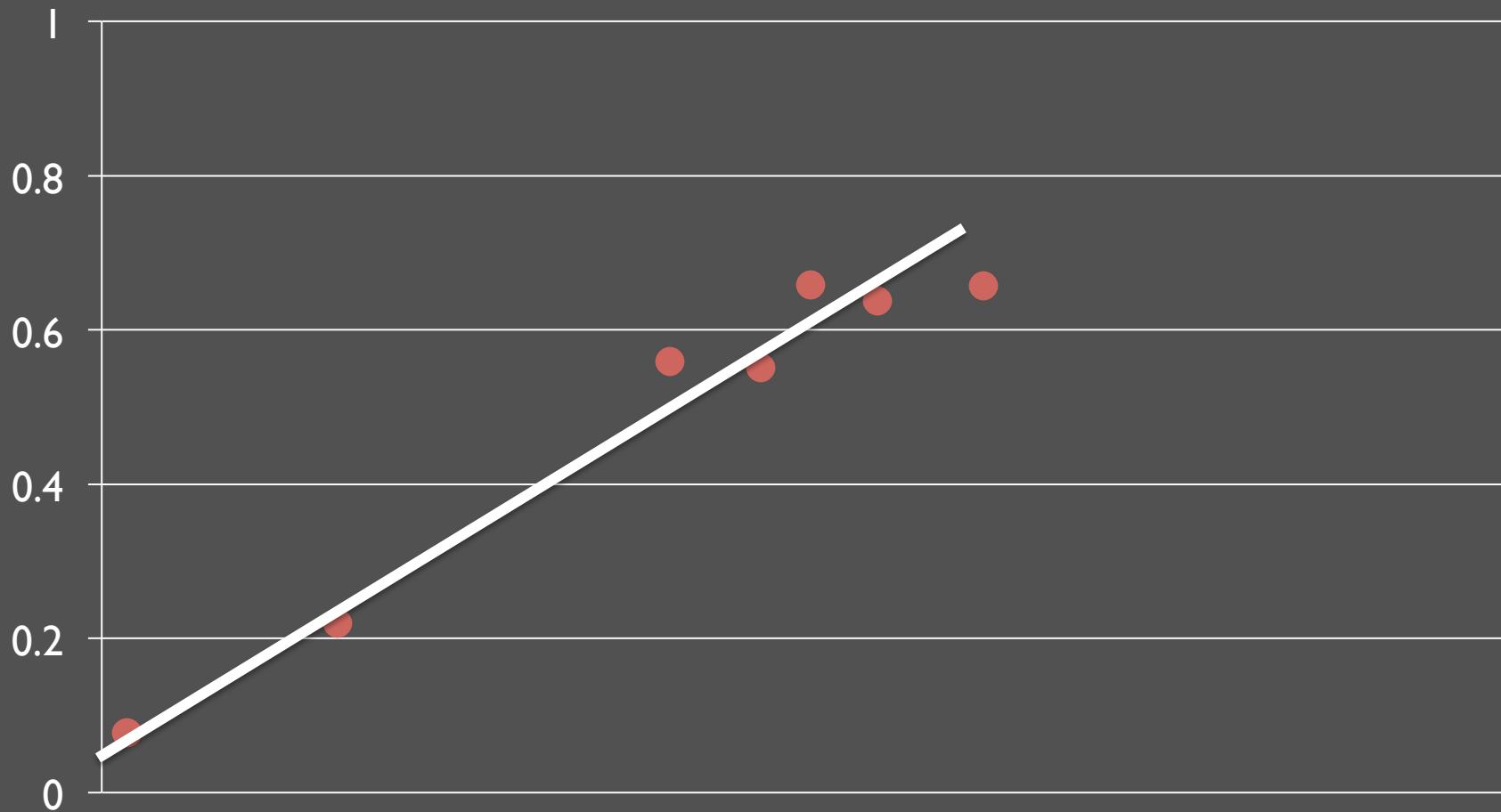
**Decision Uncertainty:** "We're not sure what to do now that we have the data"



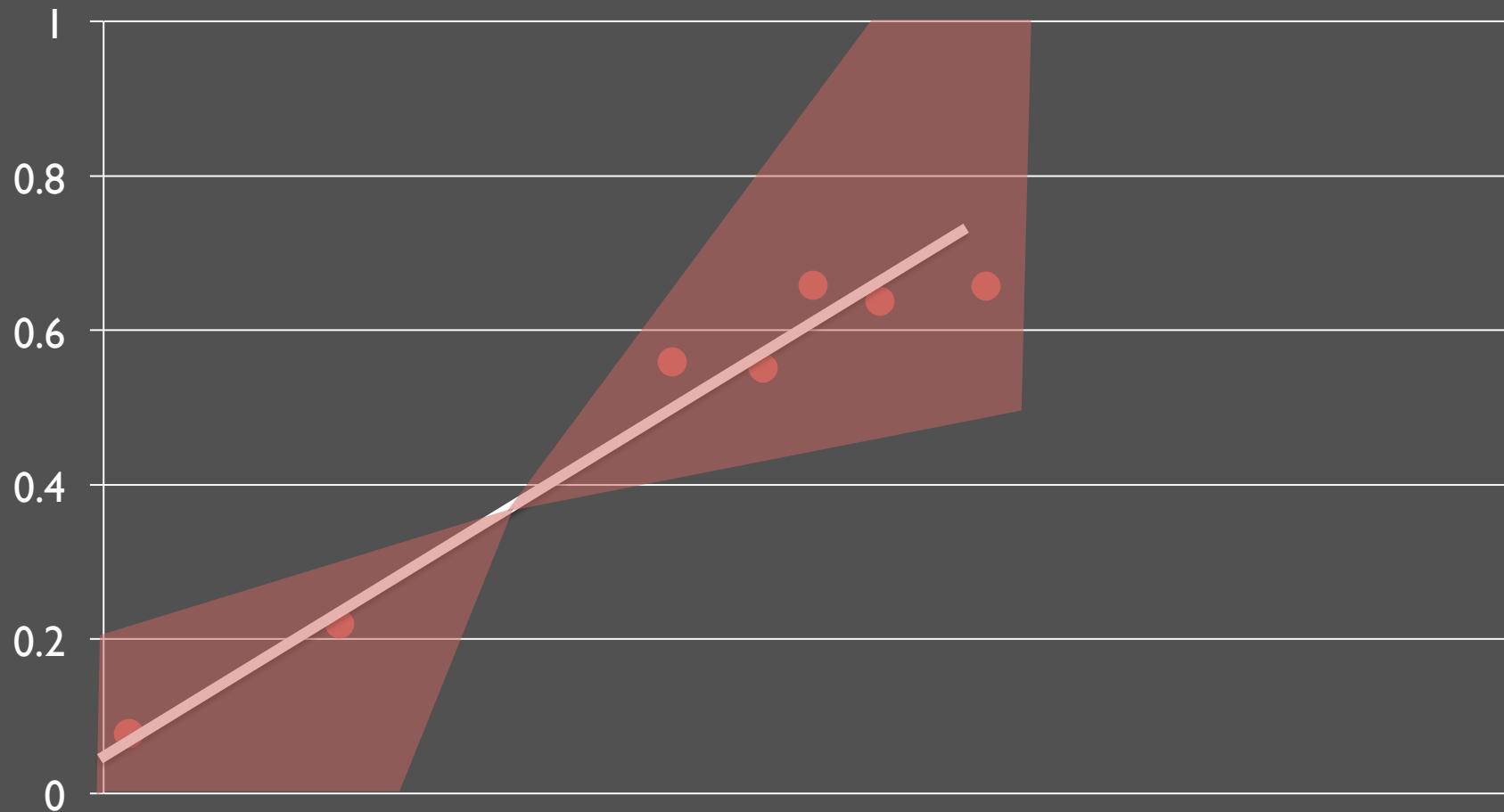
# Measurement Uncertainty



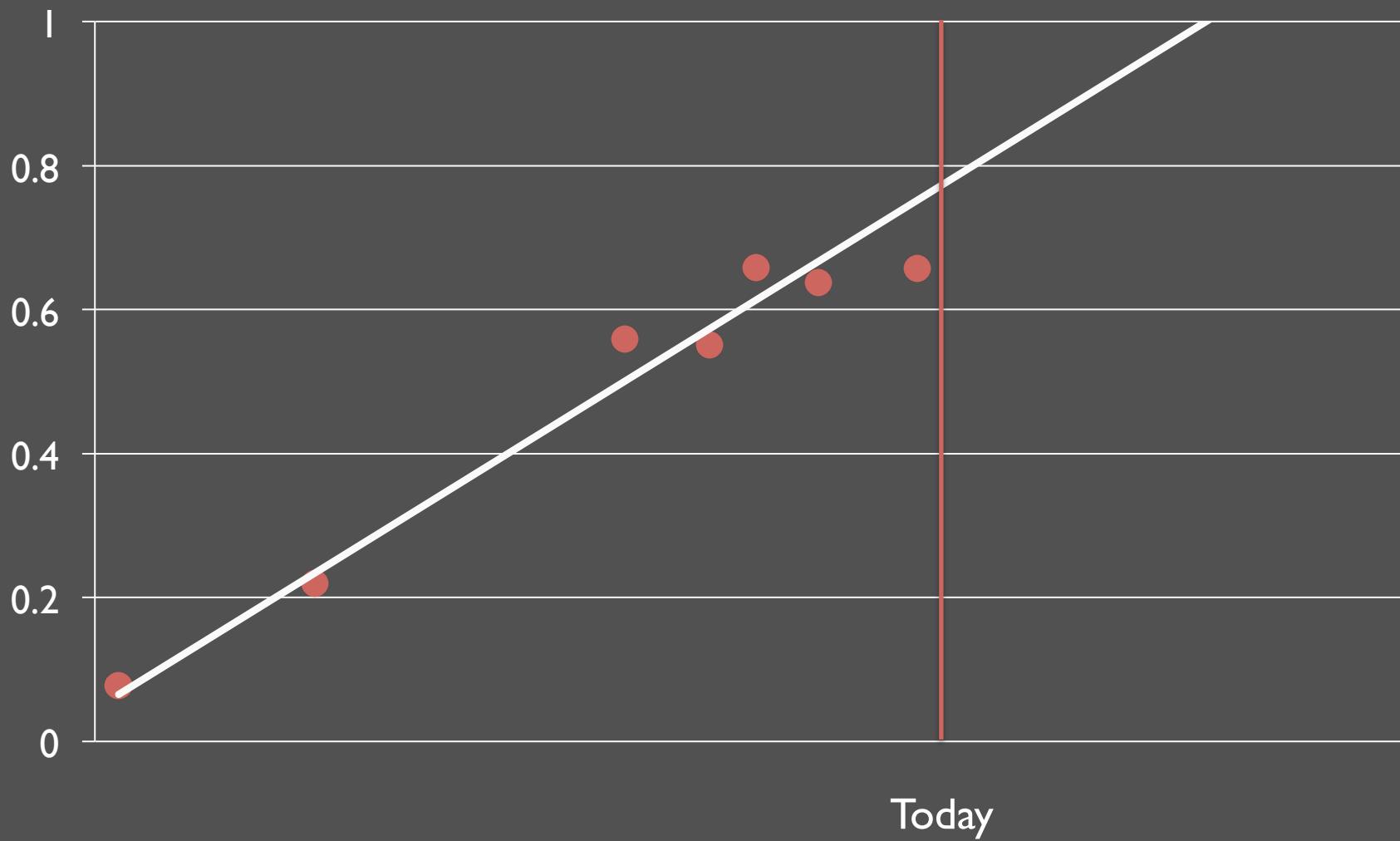
# Model Uncertainty



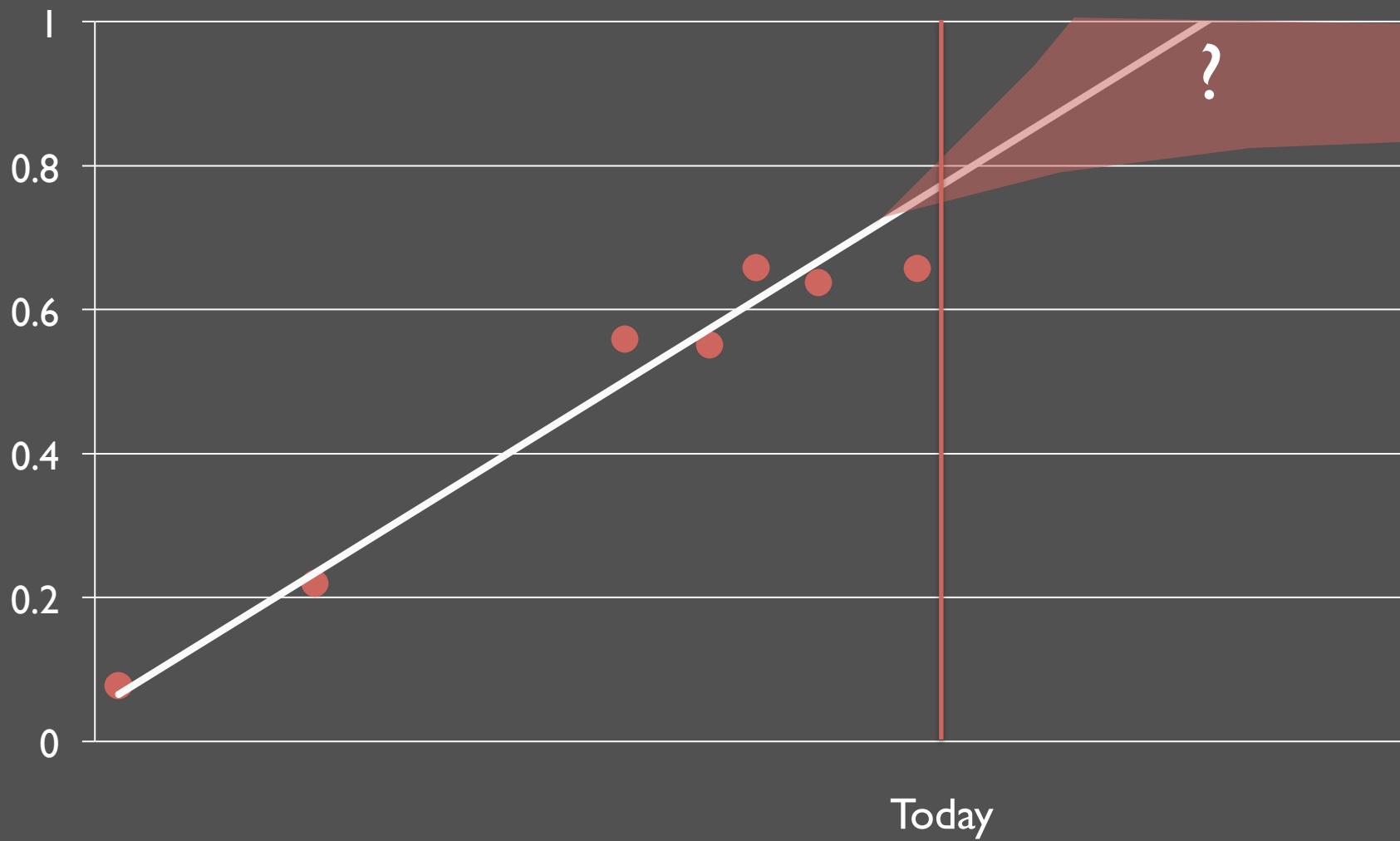
# Model Uncertainty



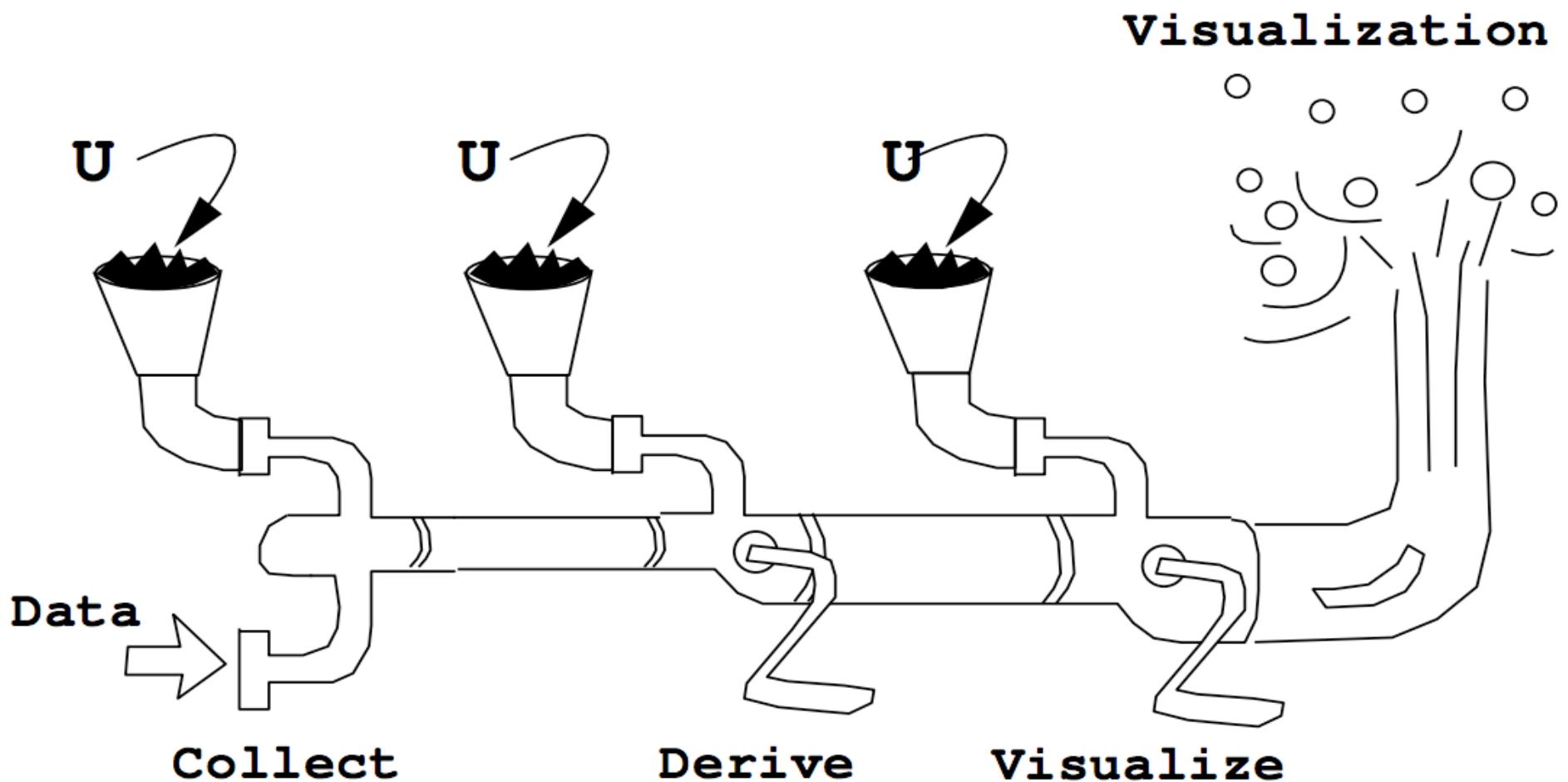
# Decision Uncertainty



# Decision Uncertainty



# Uncertainty Vis Pipeline

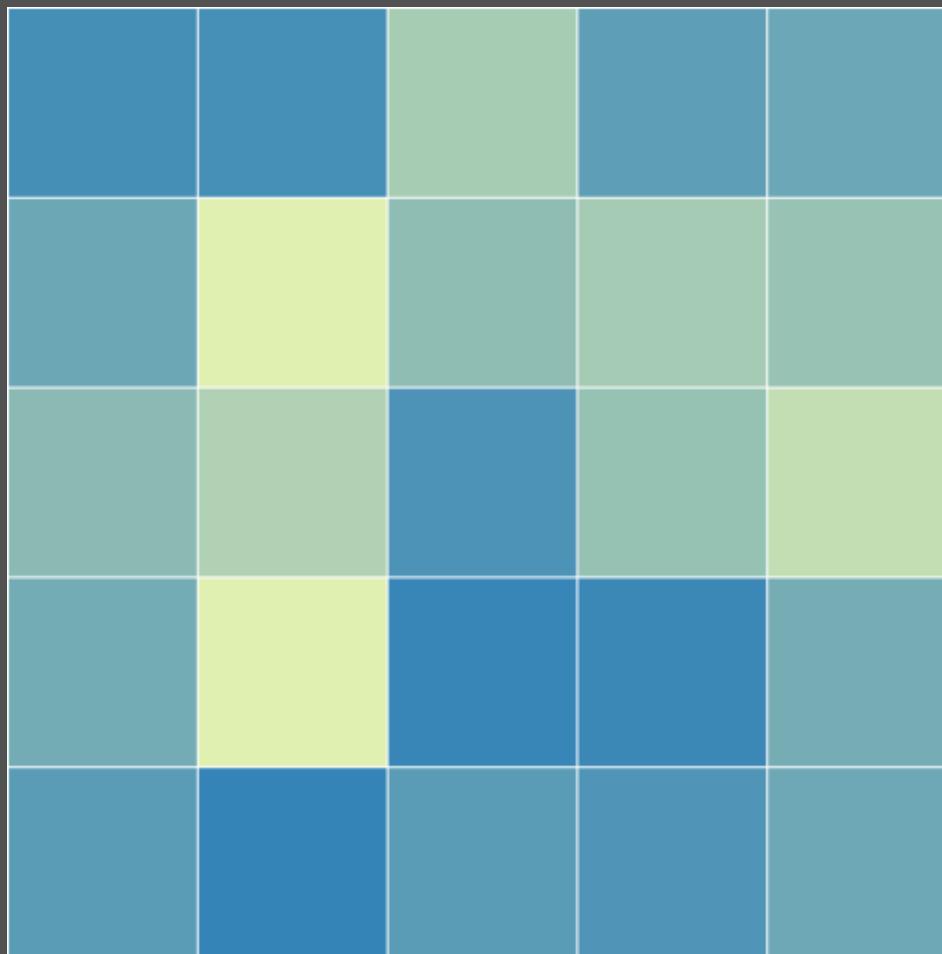


Pang et al. Approaches to Uncertainty Visualization. *The Visual Computer*, 1997.

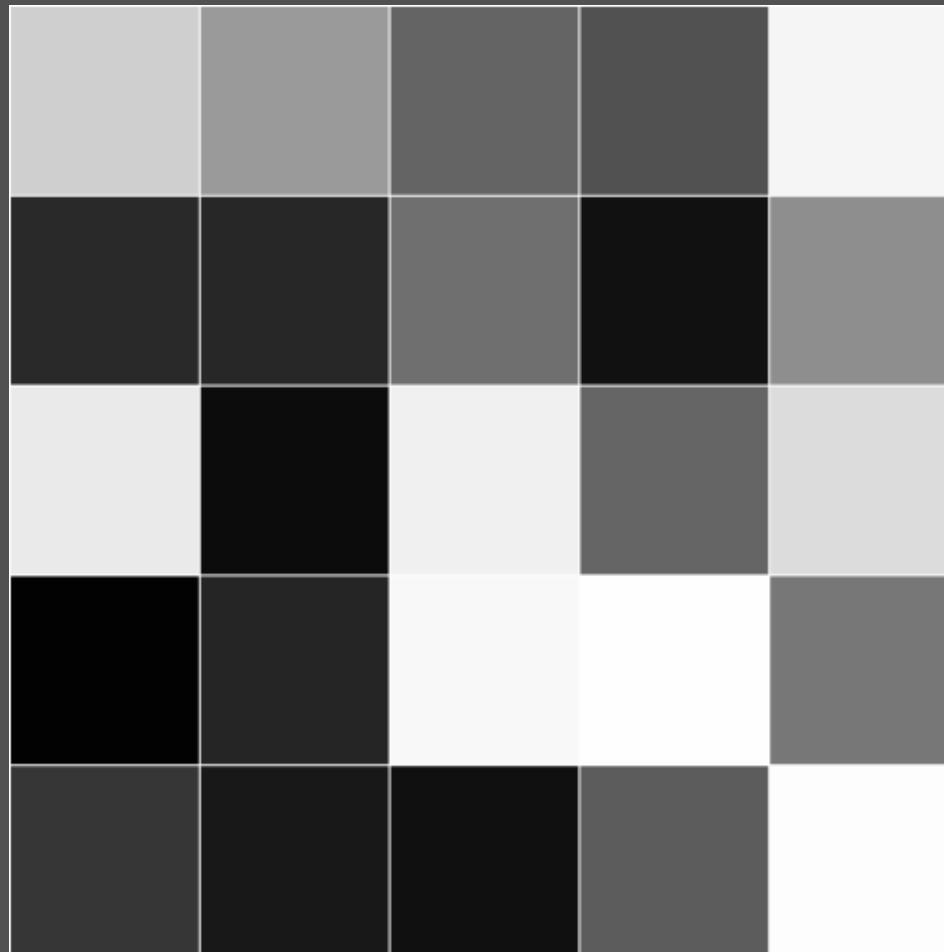
# Uncertainty Vis Pipeline

- 1) Quantify Uncertainty
- 2) Choose a free visual variable
- 3) Encode uncertainty with the variable

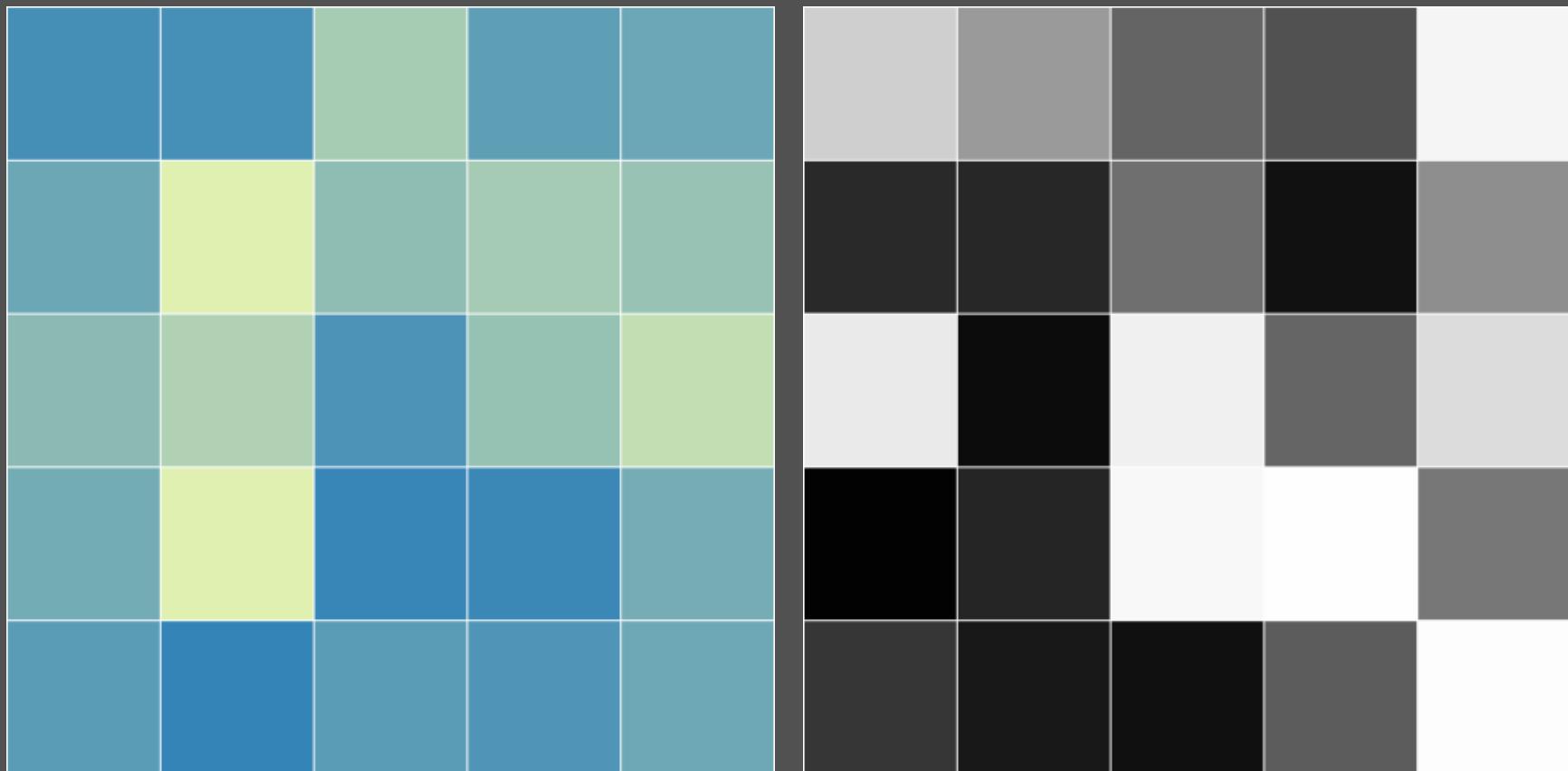
# Data Map



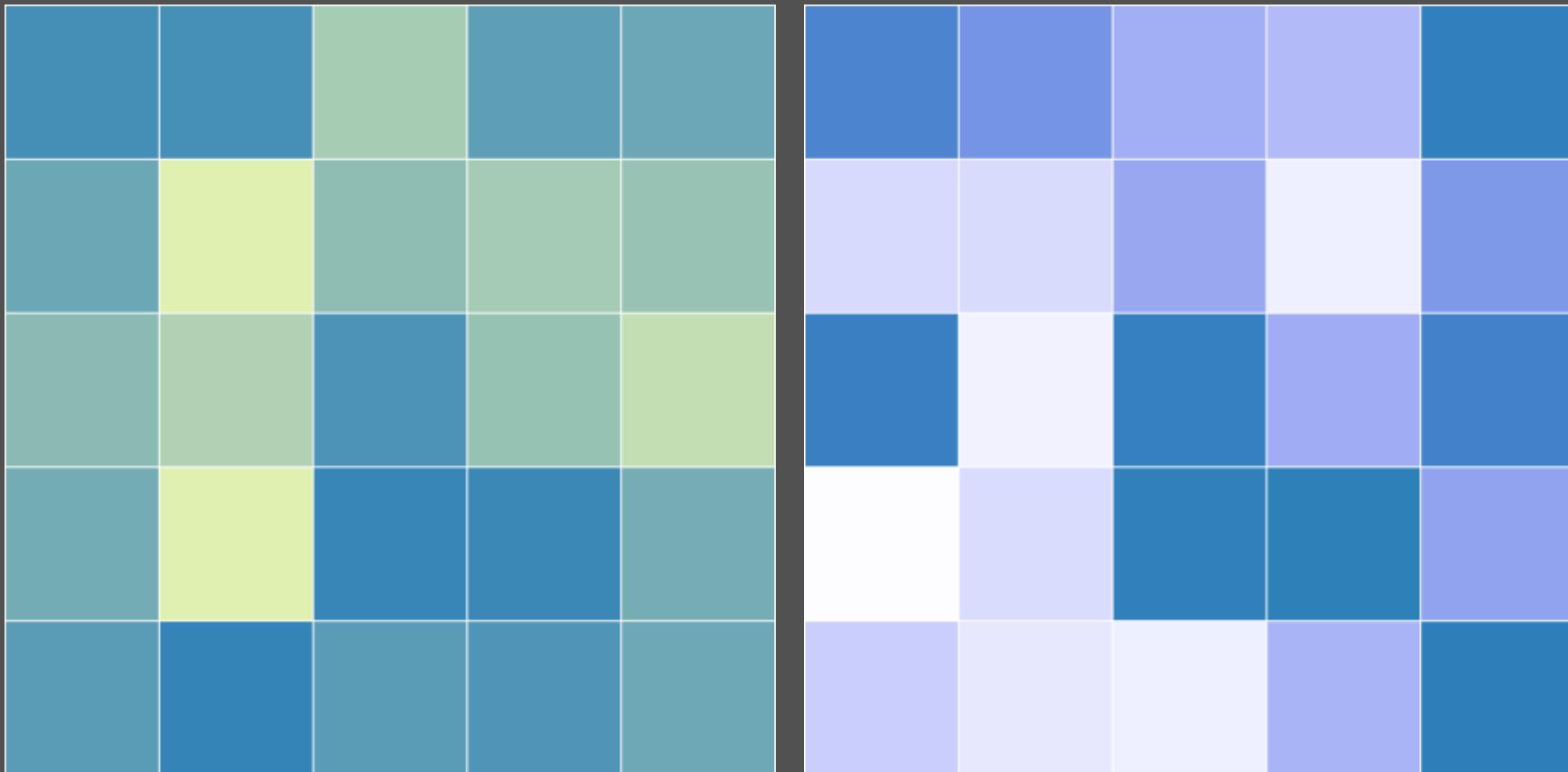
# Uncertainty Map



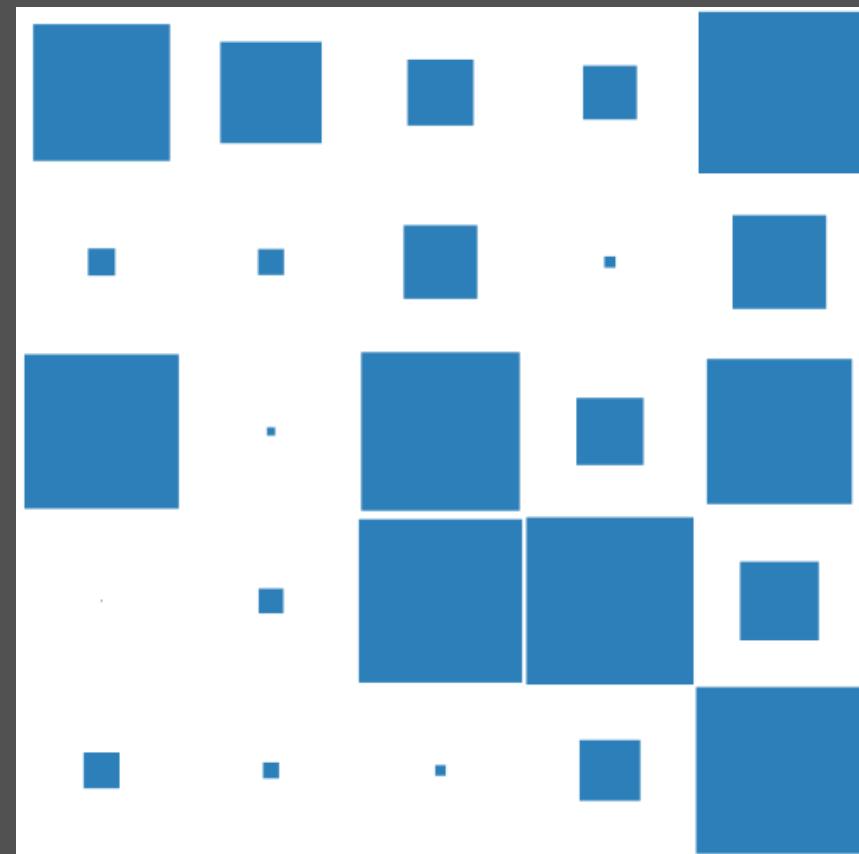
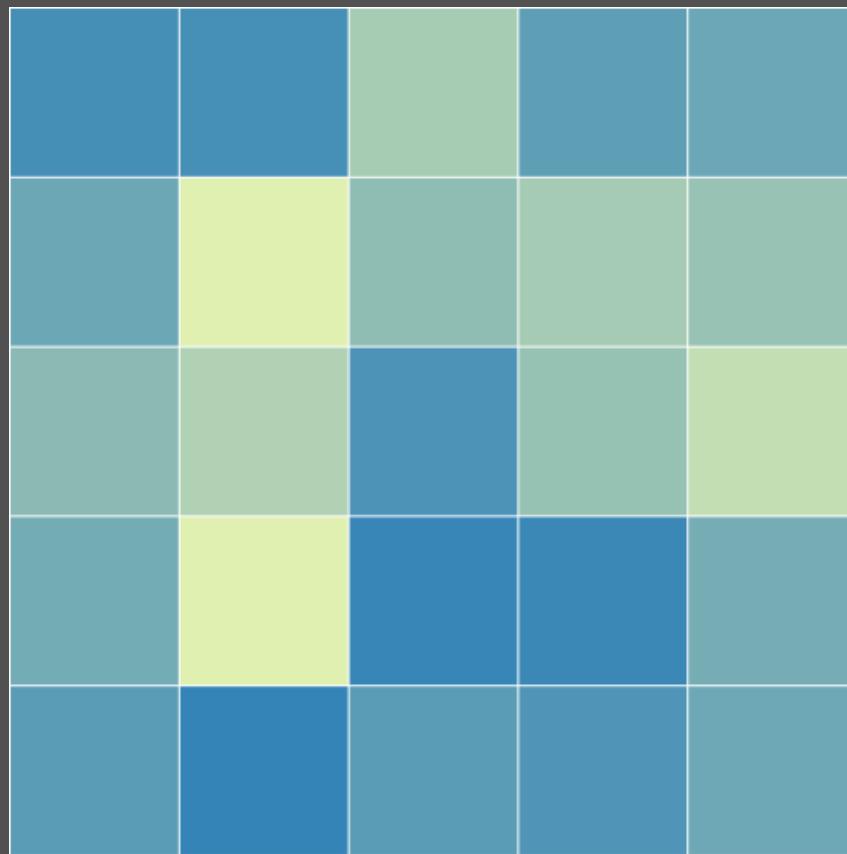
# Juxtaposition



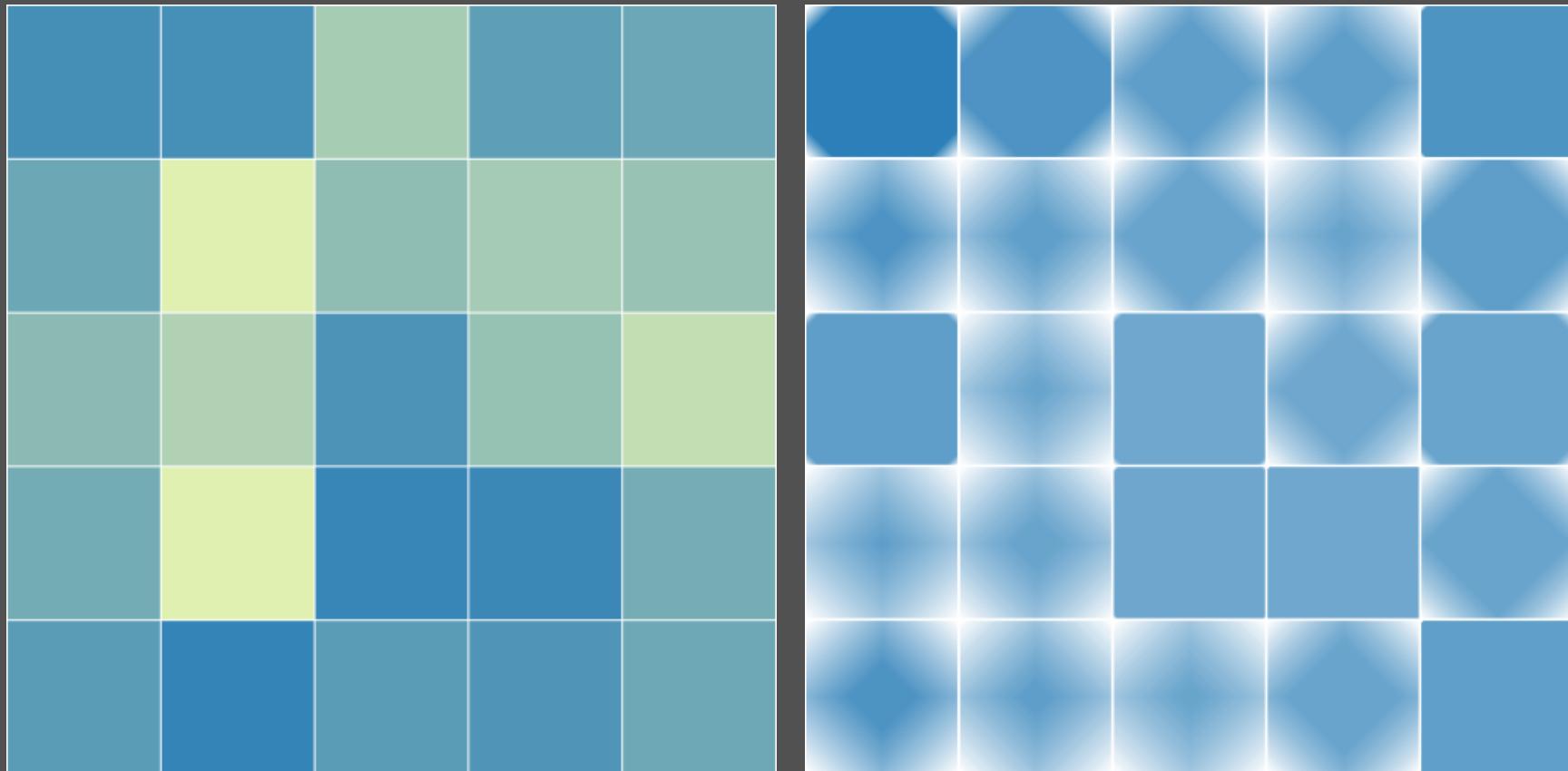
# Juxtaposition



# Juxtaposition



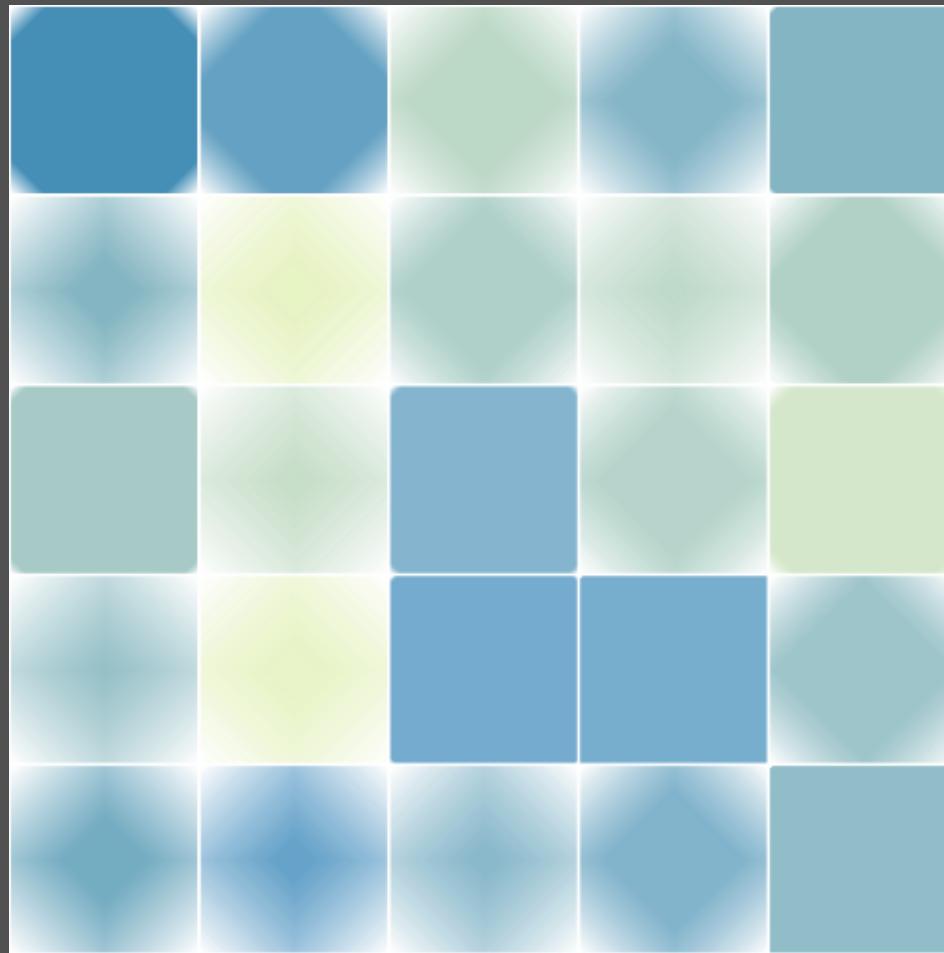
# Juxtaposition



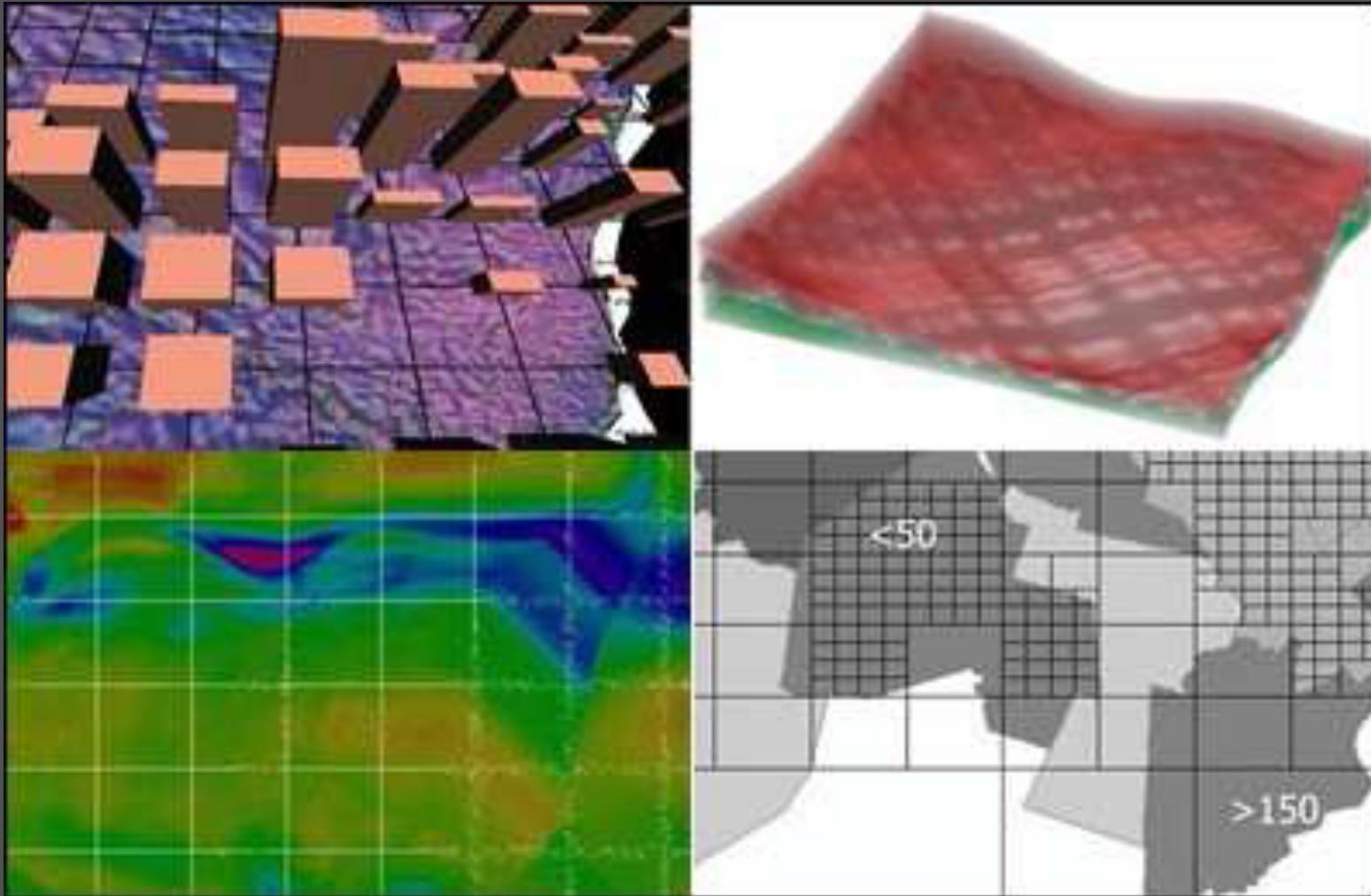
# Superposition



# Superposition



# Superposition



Griethe, Henning and Schumann, Heidrun. The Visualization of Uncertain Data: Methods and Problems. SimVis, 2006.

# Uncertainty Vis Pipeline?

- 1) Quantify Uncertainty
- 2) Choose a free visual variable
- 3) Encode uncertainty with the variable

Design Decisions:

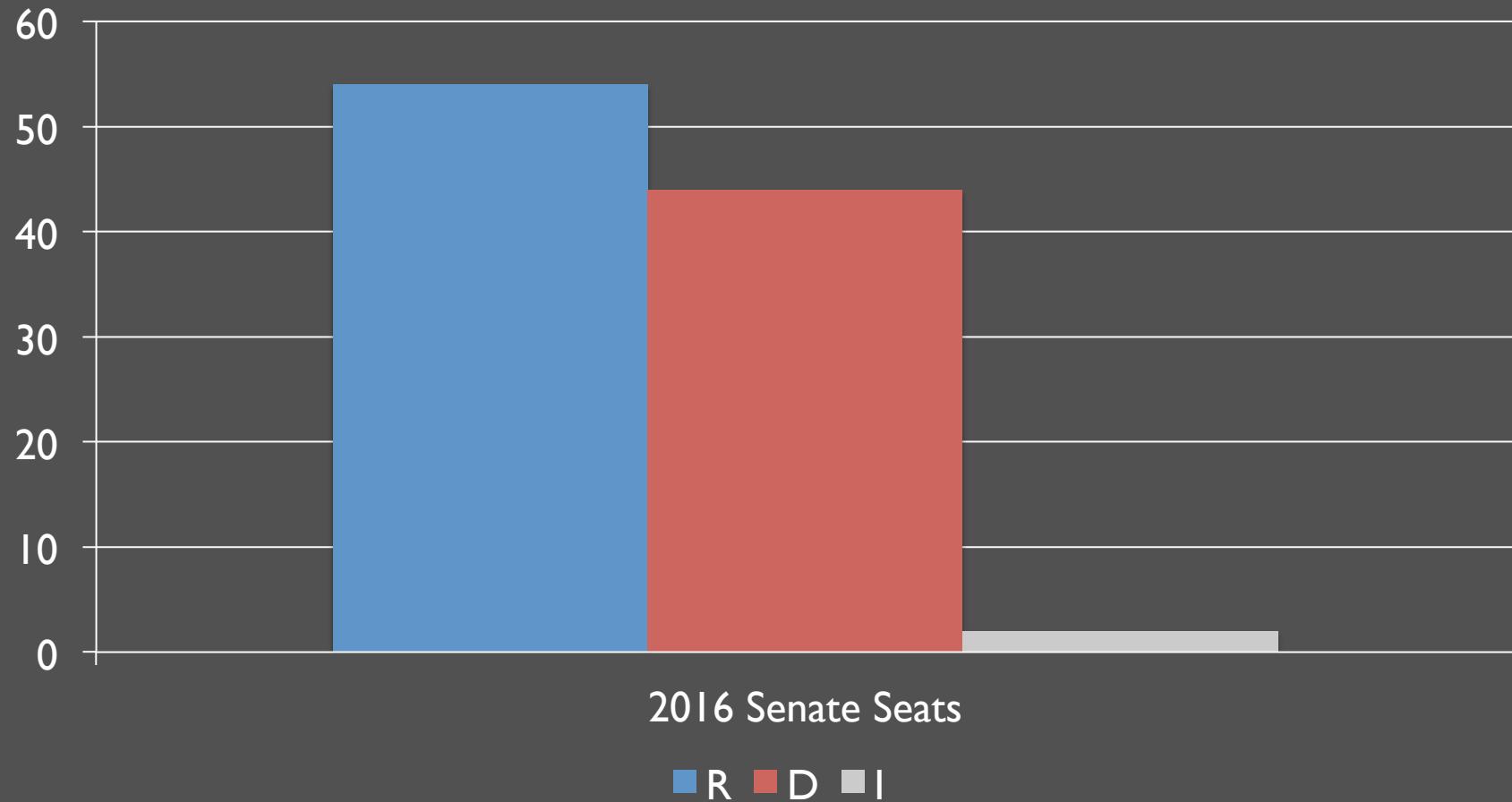
How to unify data and uncertainty map(s)?

# Semiotics of Uncertainty

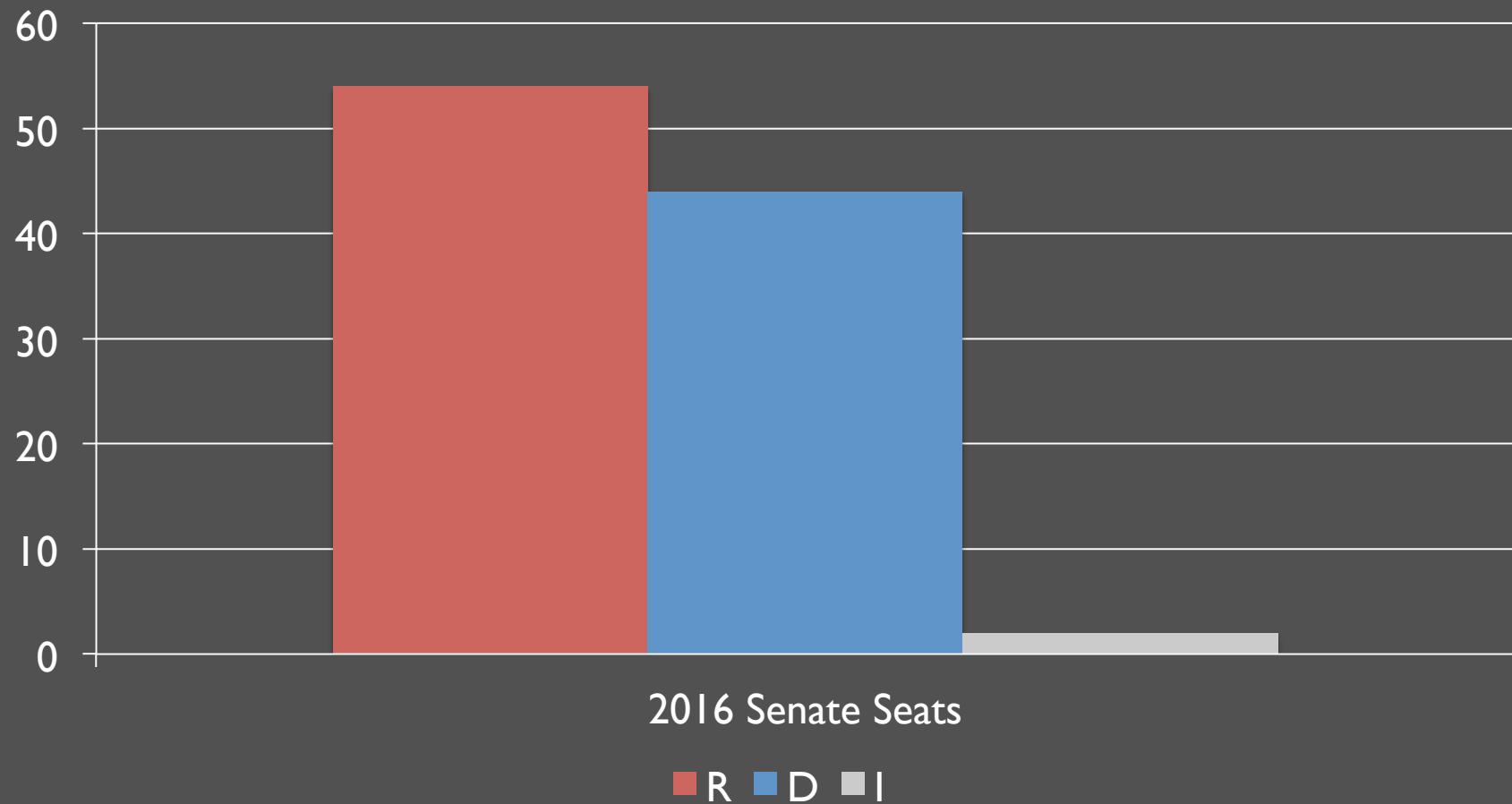


*Ceci n'est pas une pipe.*

# The Variable Matters!



# The Variable Matters!





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@CCTV\_America

CCTV\_America

CCTV America

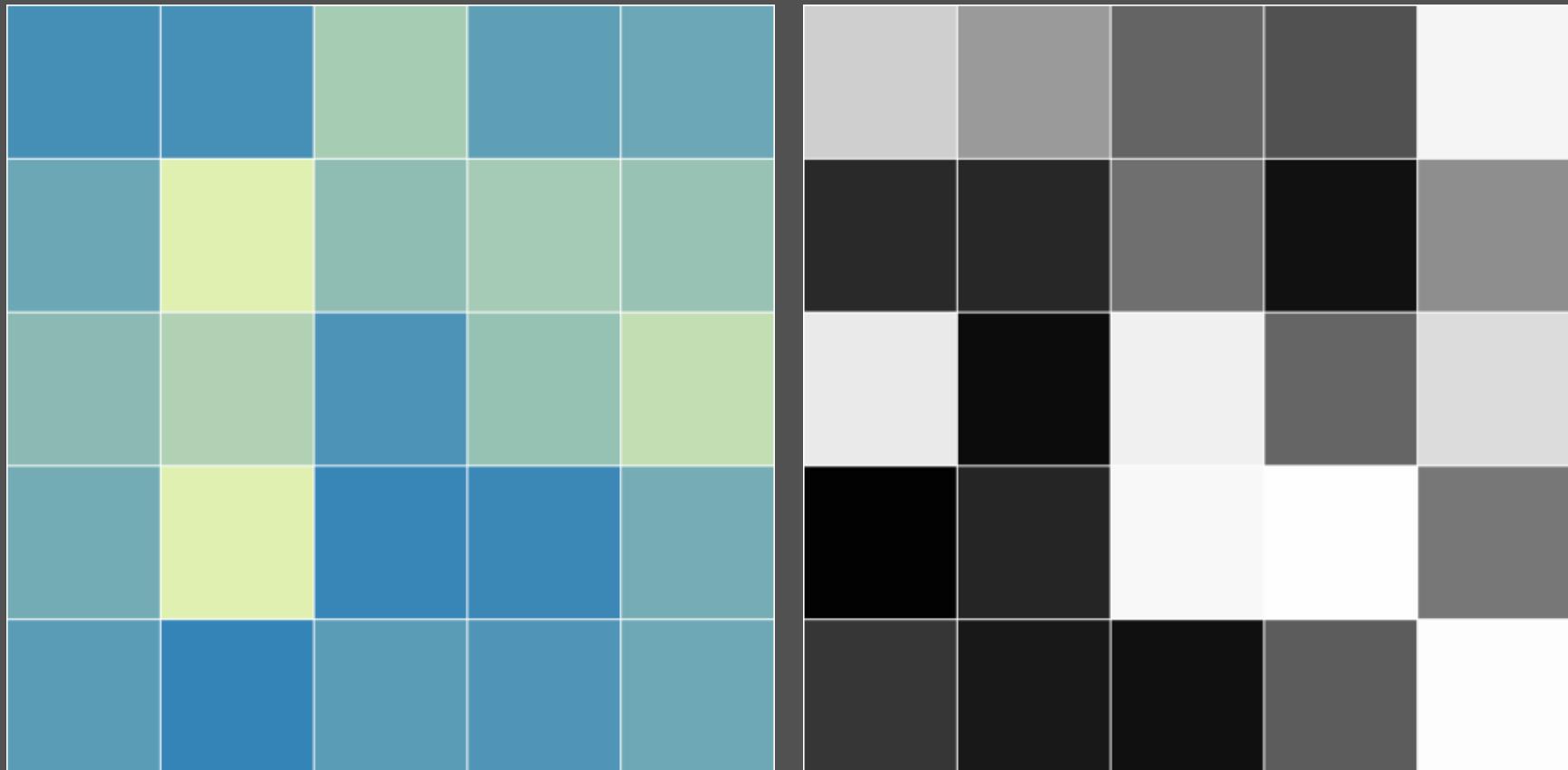


7:24 ET  
MAY 30

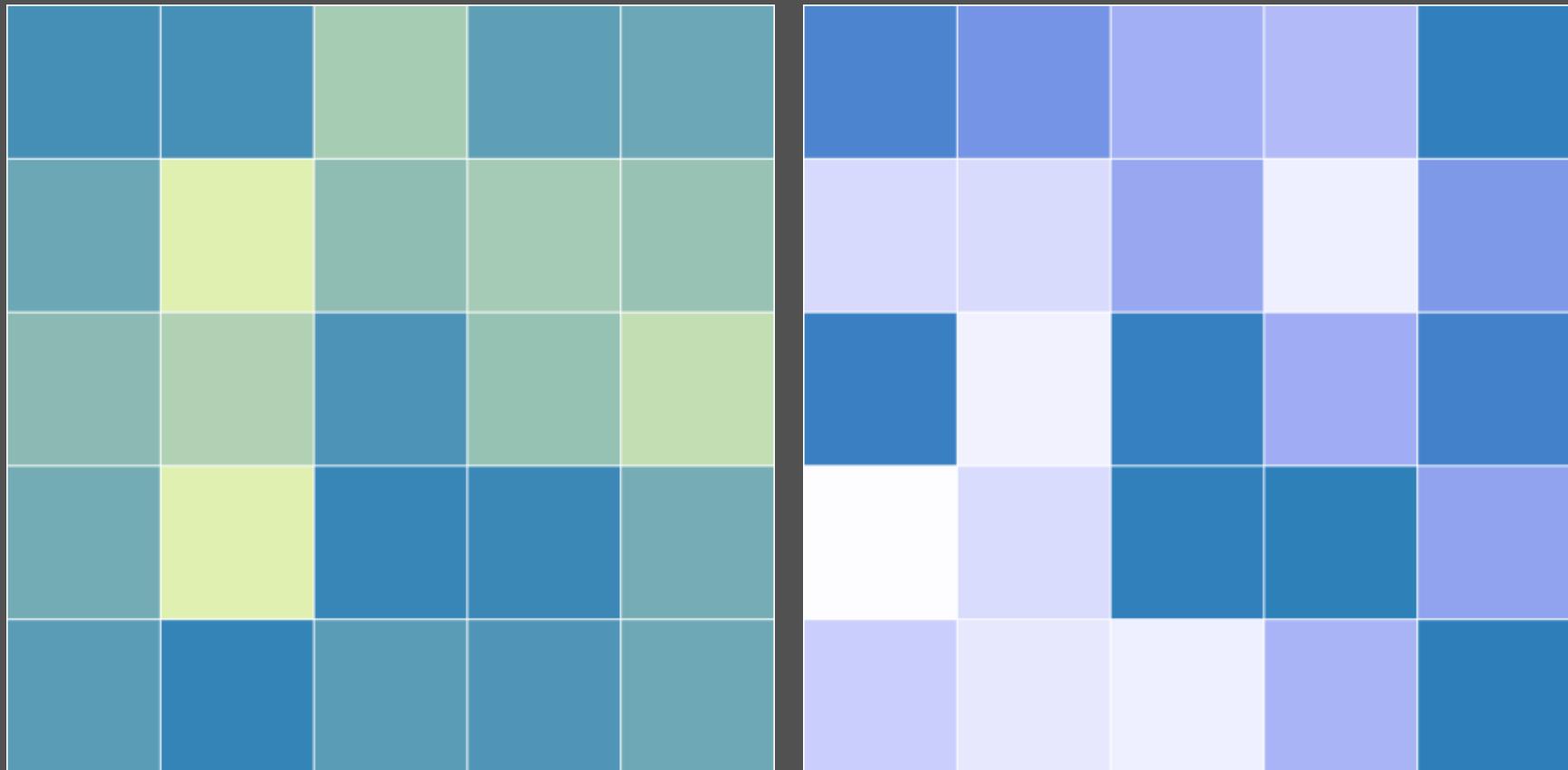
COSTCO QUARTERLY PROFIT RISES 19% ON  
INCREASED REVENUE FROM MEMBERSHIP FEES

Gold	Silver	Plat.	Copper	Alum.
1415.25 ▲ 1.11	22.76 ▲ 0.07	1482.70 ▼ 1.00	331.35 ▼ 0.20	1907.00 ▲ 44.00

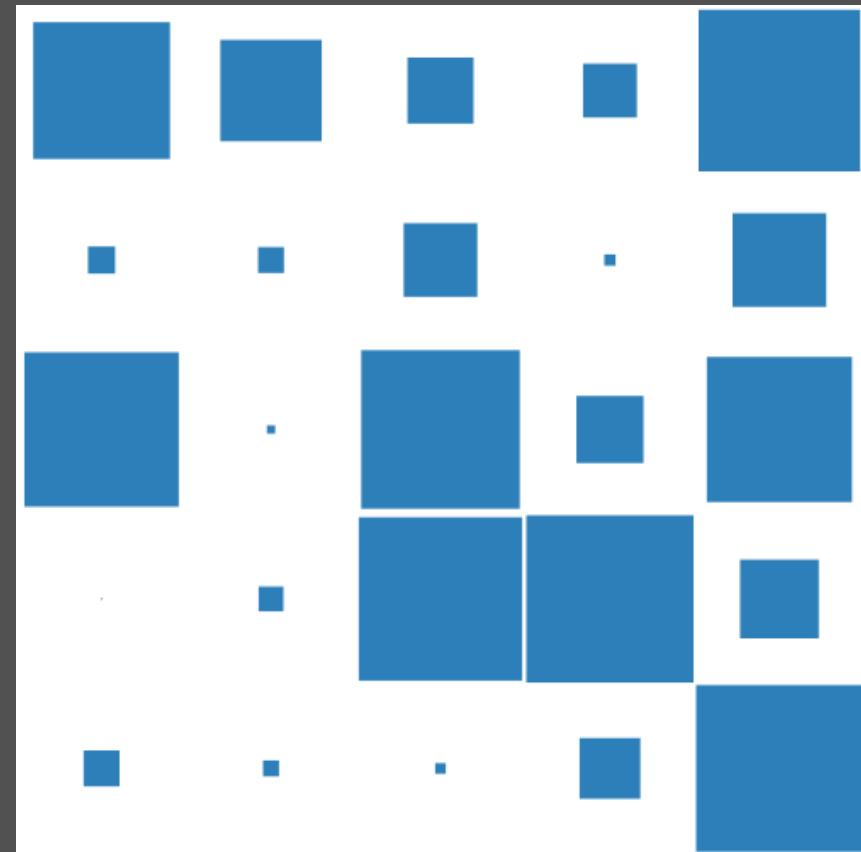
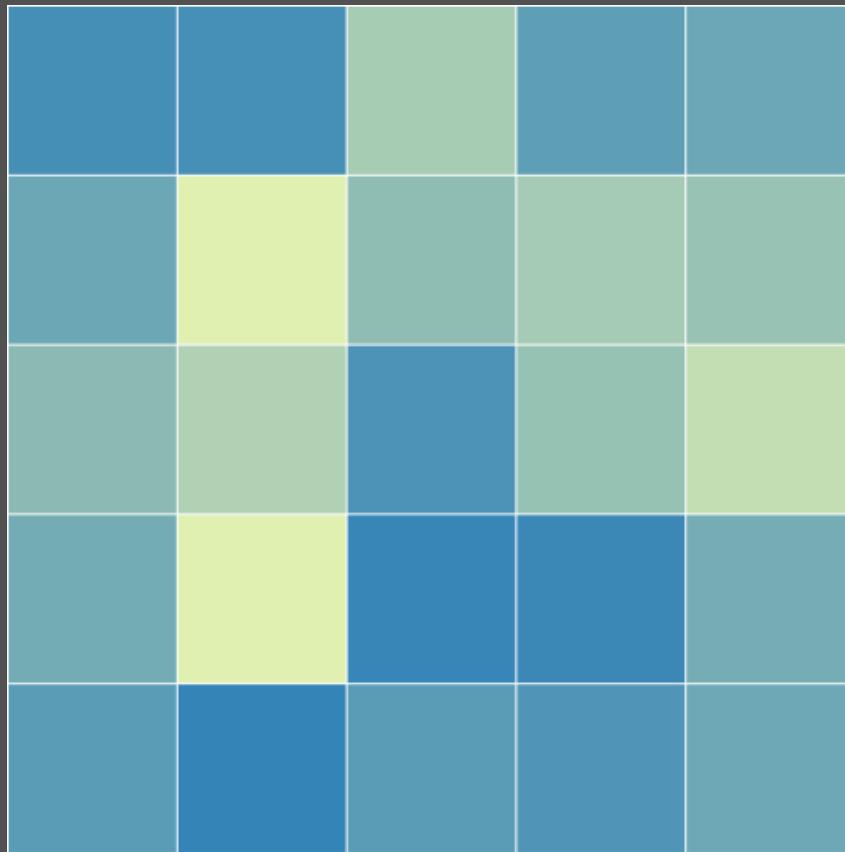
# Visual Variables for Uncertainty



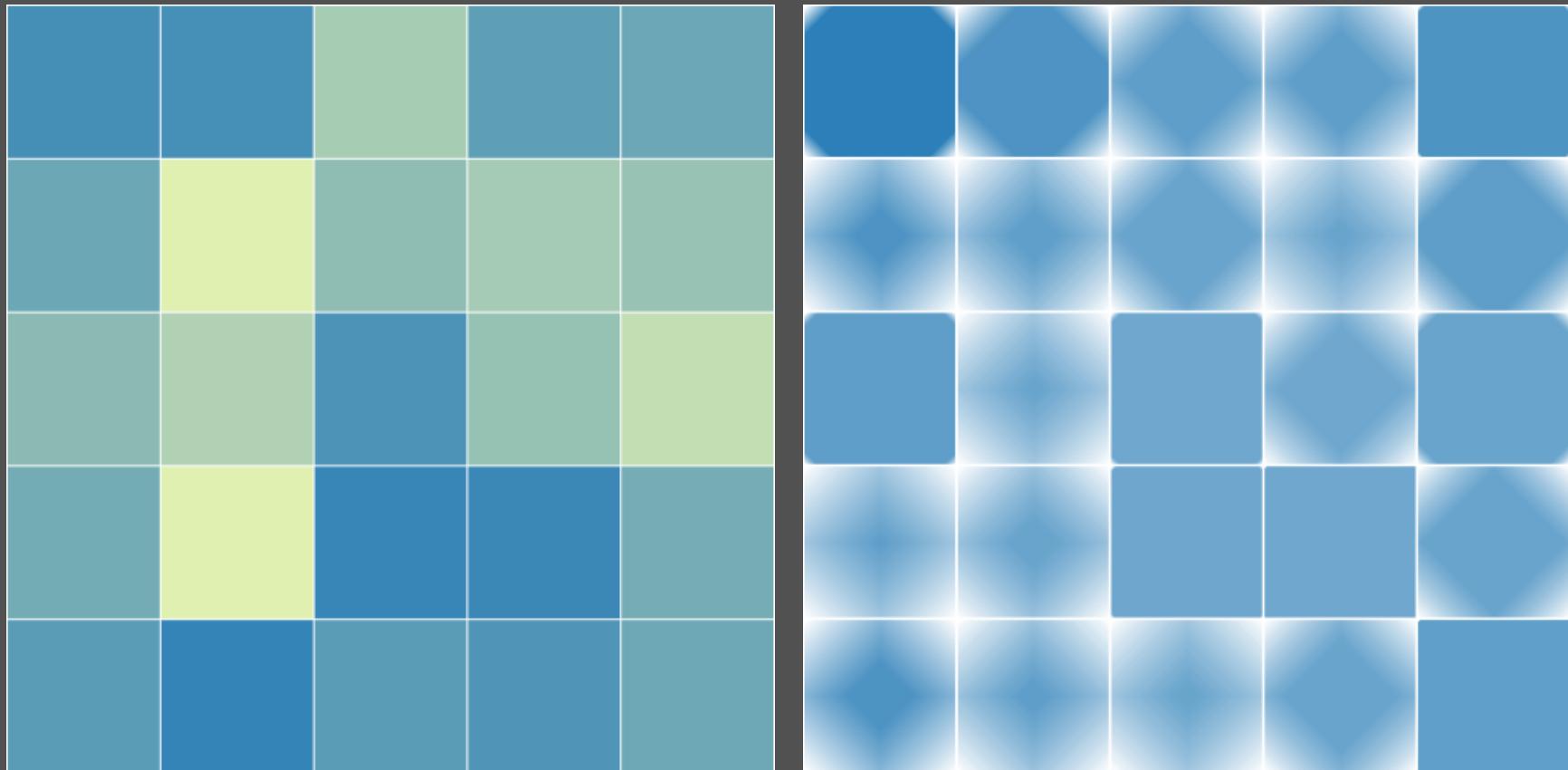
# Value



# Size



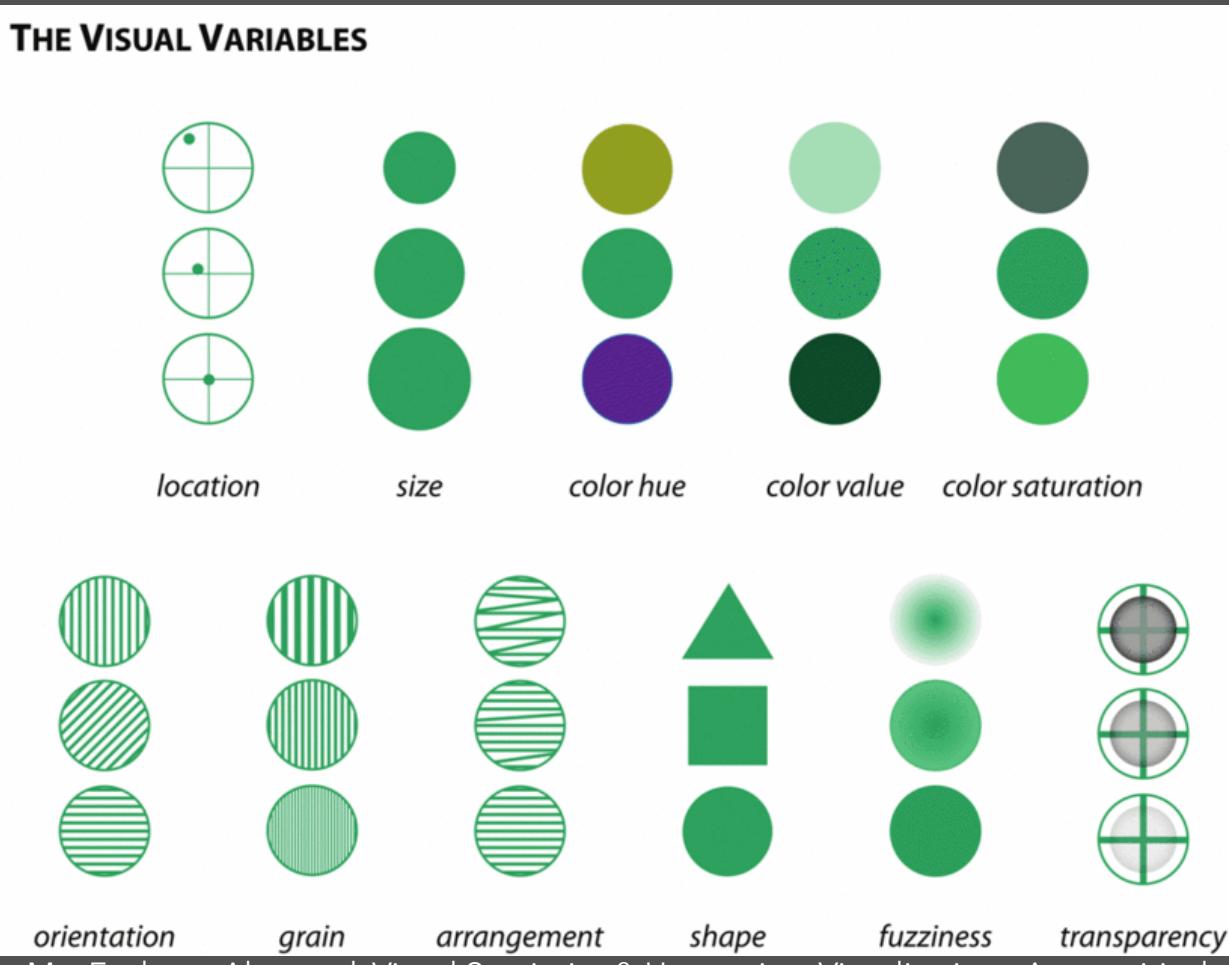
# Fuzziness



# Semiotics of Uncertainty

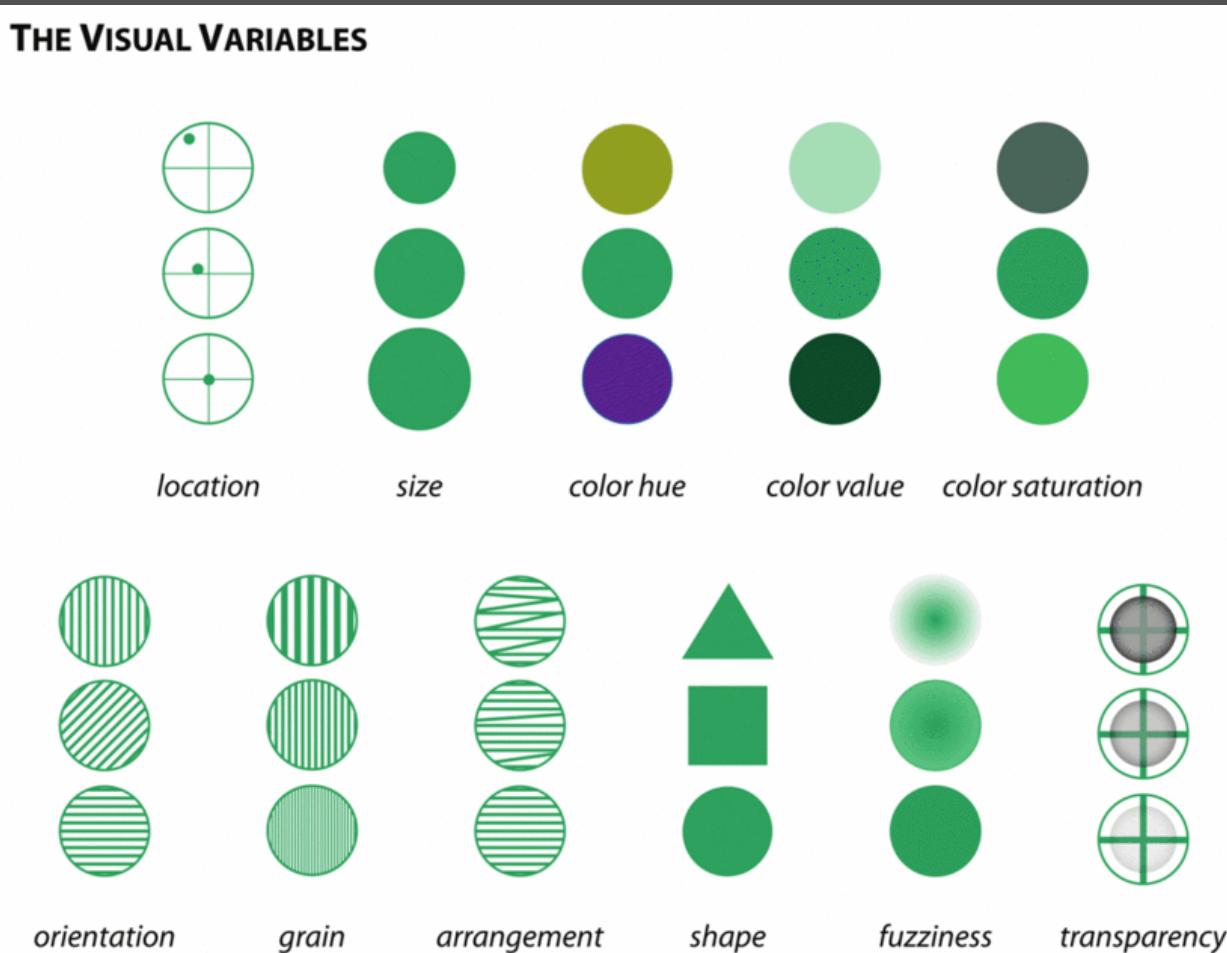


# Semiotics of Uncertainty

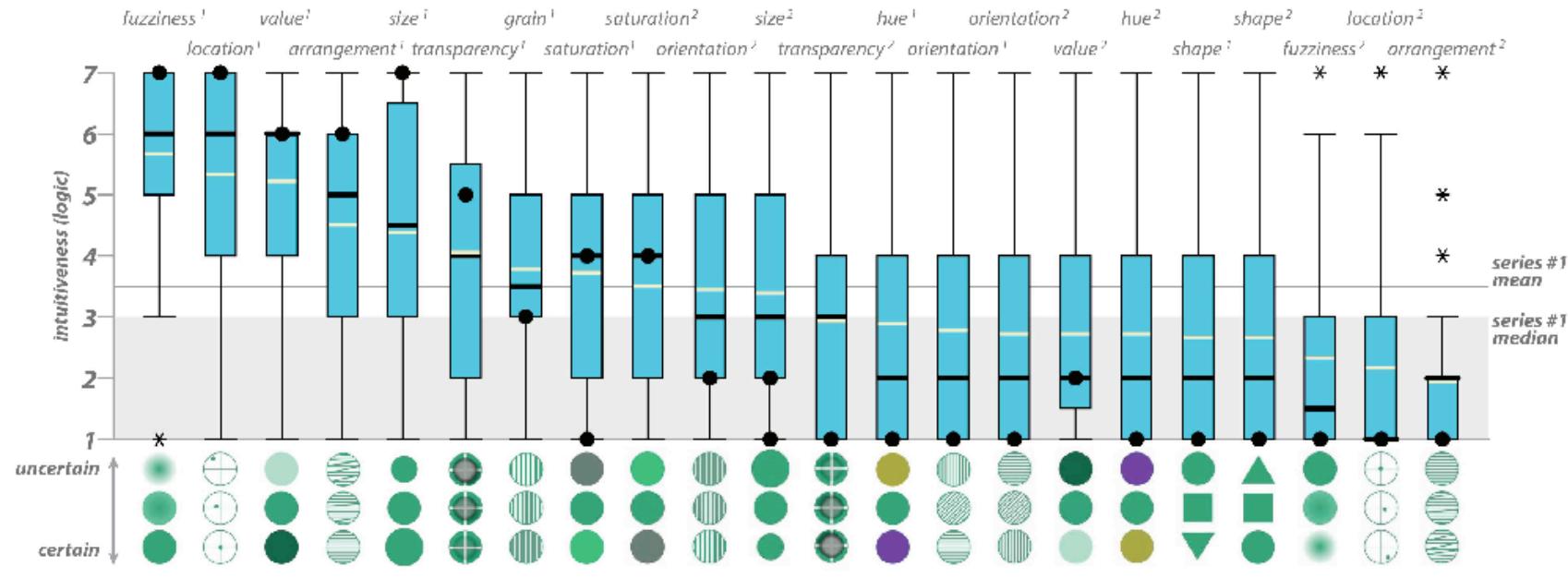


MacEachren, Alan et al. Visual Semiotics & Uncertainty Visualization: An empirical study. IEEE VIS, 2012.

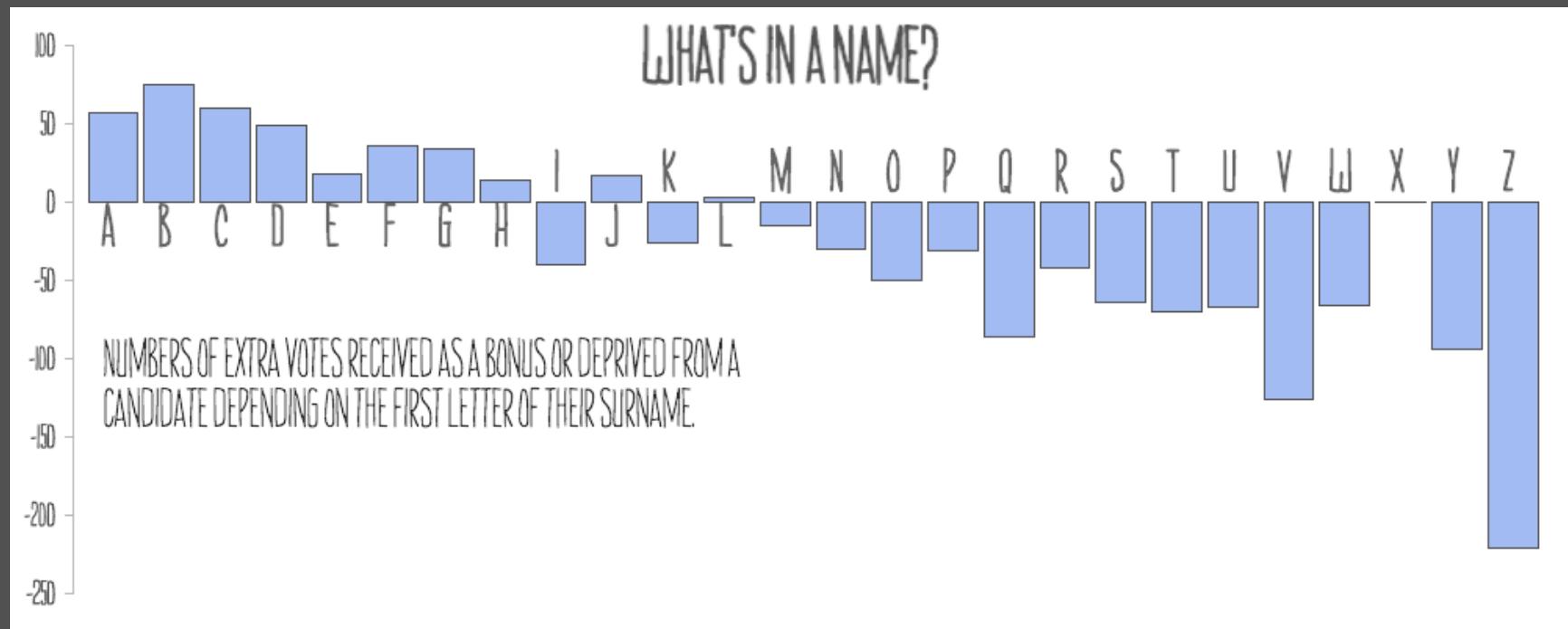
# Semiotics of Uncertainty



## SERIES #1: GENERAL UNCERTAINTY BY VISUAL VARIABLE



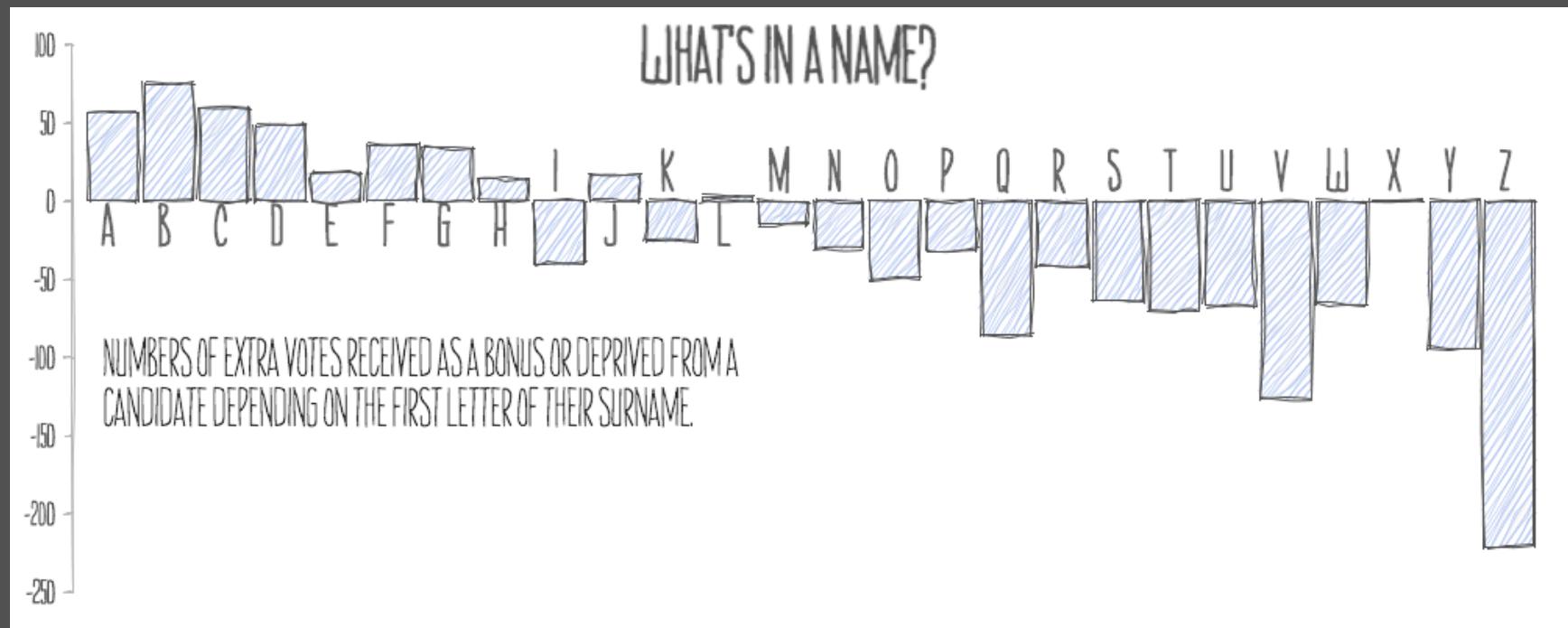
# “Sketchiness”



Wood, Jo et al. Sketchy rendering for information visualization. IEEE VIS, 2012.

Boukhelifa, Nadia et al. Evaluating sketchiness as a visual variable for the depiction of qualitative uncertainty. IEEE VIS, 2012.

# “Sketchiness”



Wood, Jo et al. Sketchy rendering for information visualization. IEEE VIS, 2012.

Boukhelifa, Nadia et al. Evaluating sketchiness as a visual variable for the depiction of qualitative uncertainty. IEEE VIS, 2012.

# Encoding Uncertainty

Some visual variables (like fuzziness and value) have a **semiotic connection** to uncertainty.

However, intuitive variables may not always be accurately interpreted!

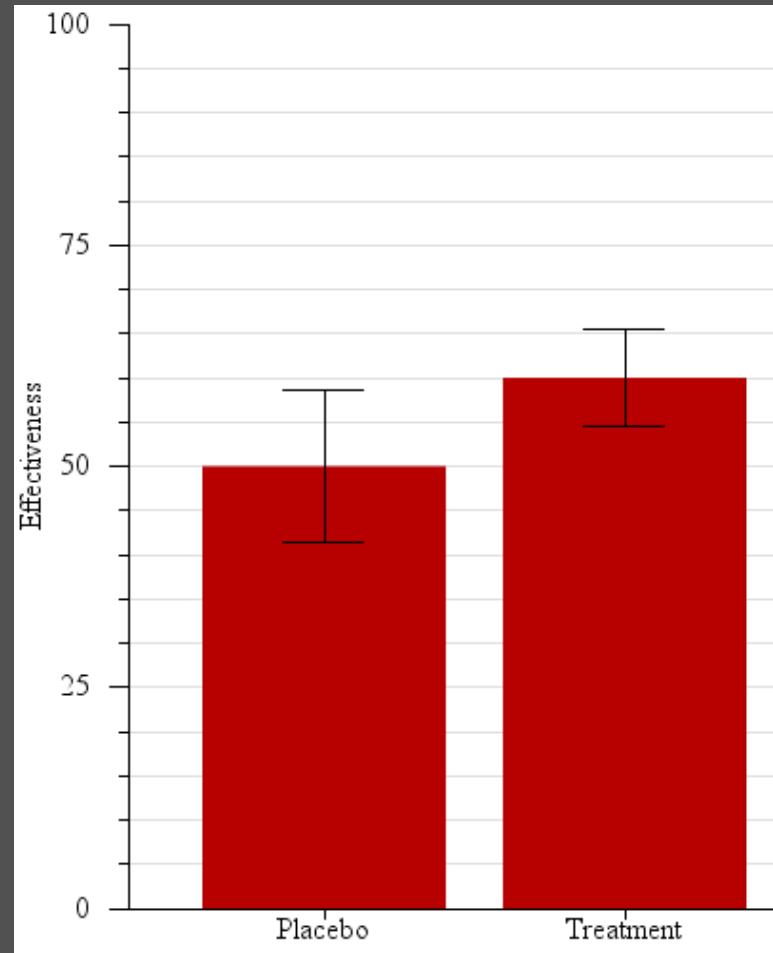
# p-value

The probability of results at least as extreme as the observed results, given some null hypothesis.

If  $p < \alpha$  (usually 0.05), then the result is considered to be *statistically significant*.

# Error Bars

Is the treatment  
*statistically significantly*  
better than the  
placebo?



# Error Bars

Standard Deviation?

Standard Error ( $\sigma/\sqrt{n}$ )

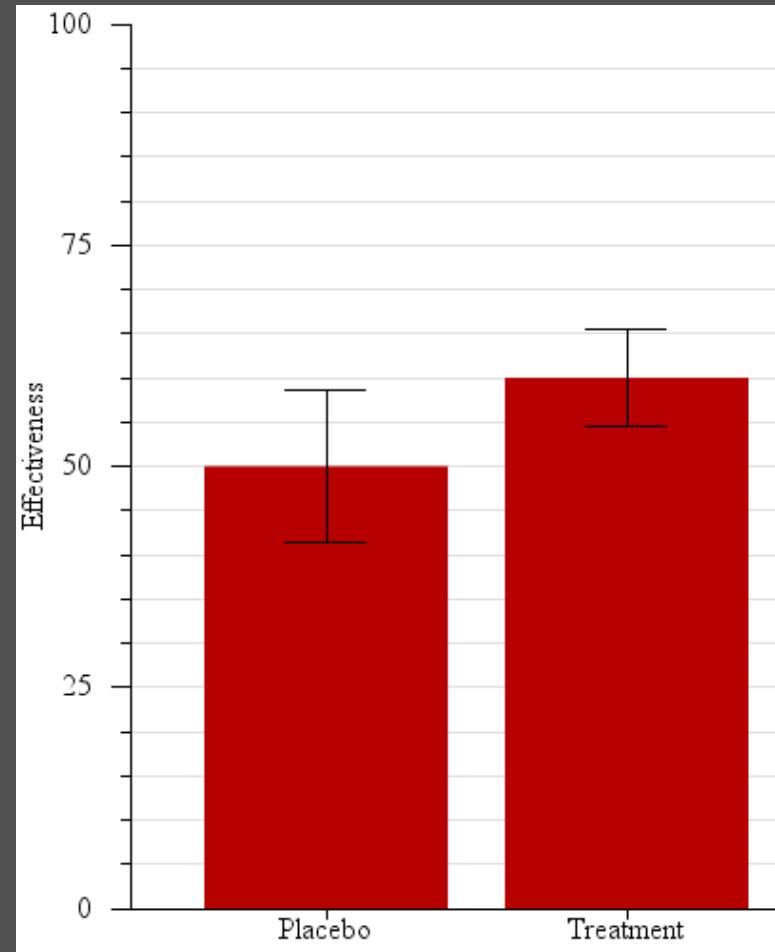
T-Confidence Interval?

Z-Confidence Interval?

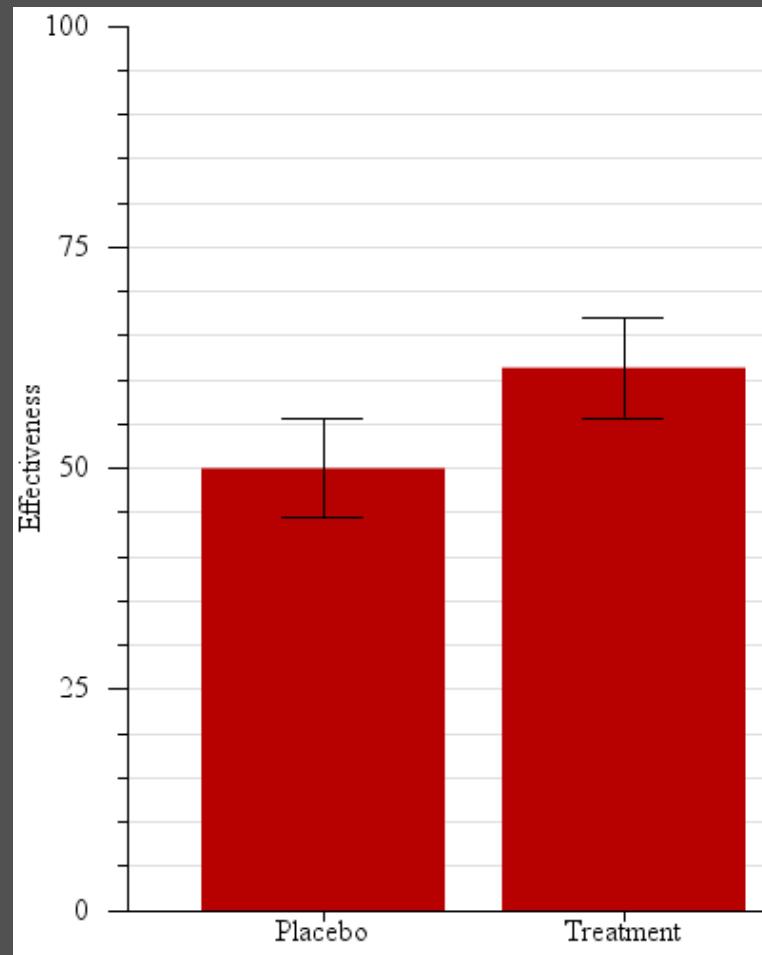
Bootstrapped Interval?

Min/Max?

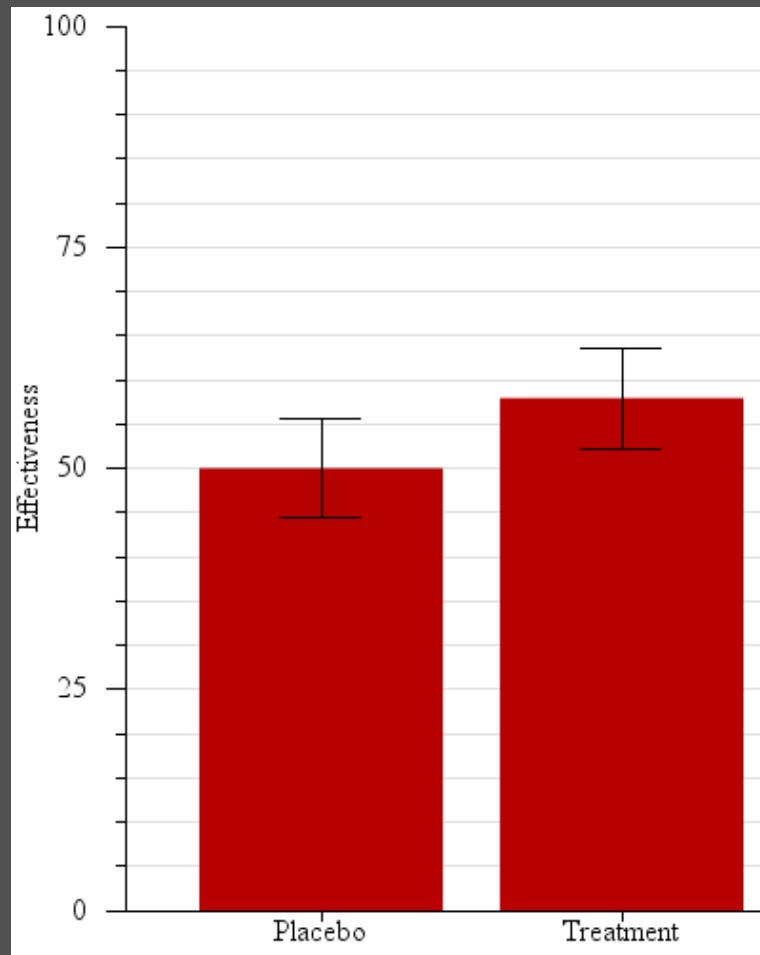
1.5\*IQR (Q3-Q1)?



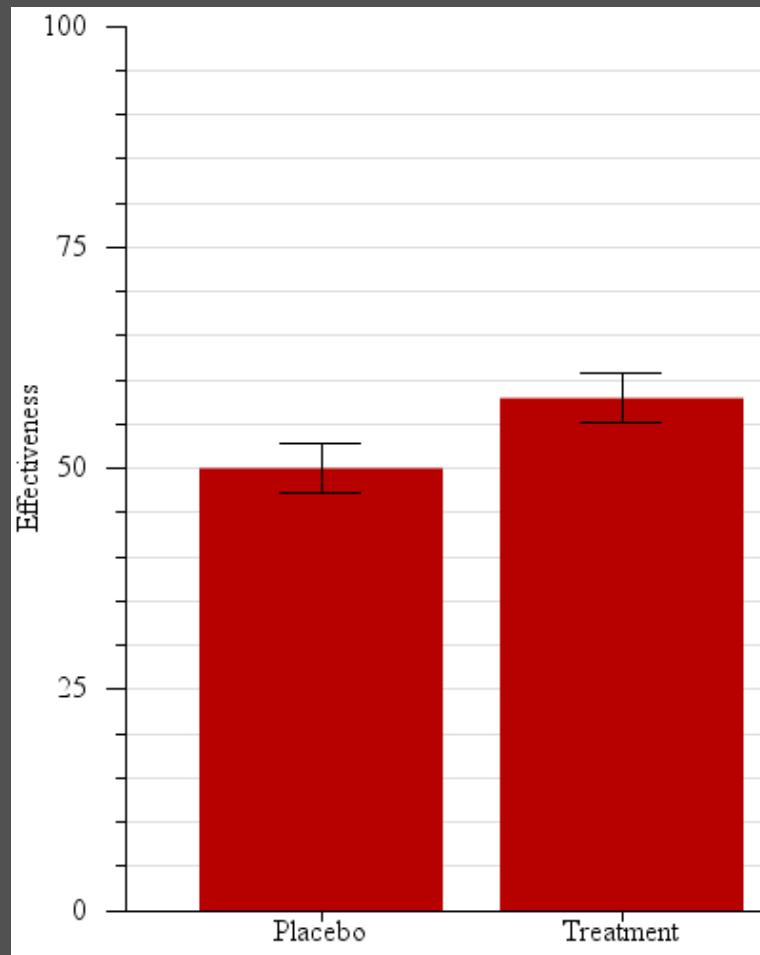
# Guess the p-value



# Guess the p-value

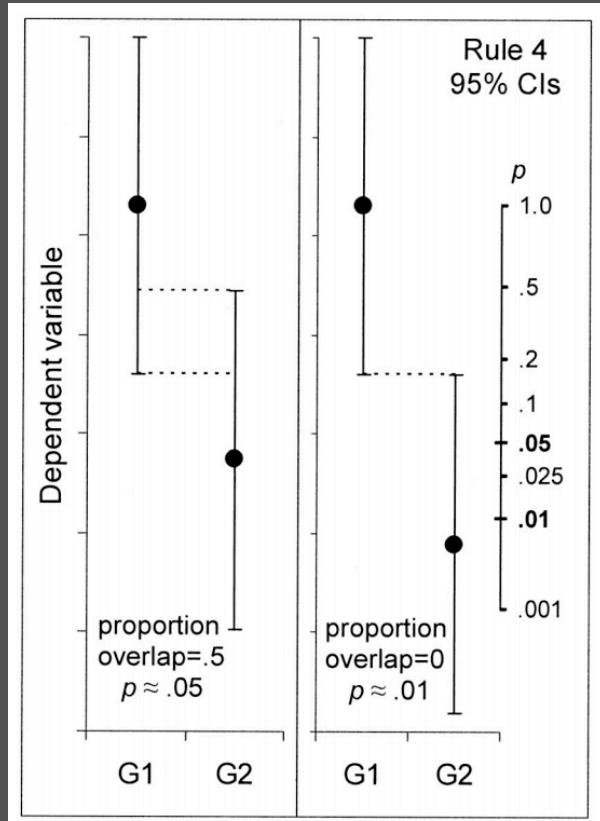


# Guess the p-value

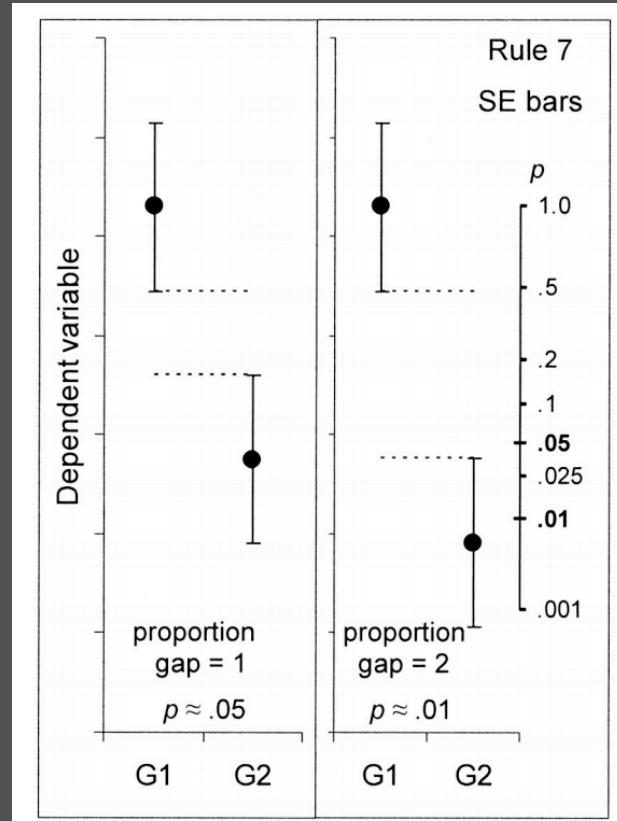


# Inference by Eye

## 95% CIs



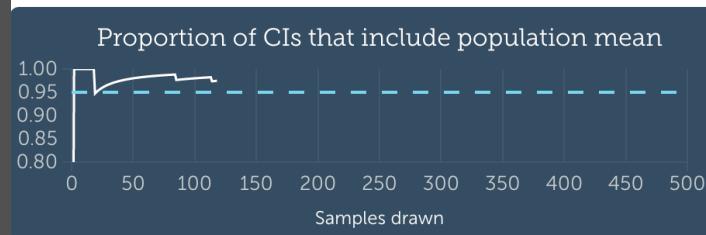
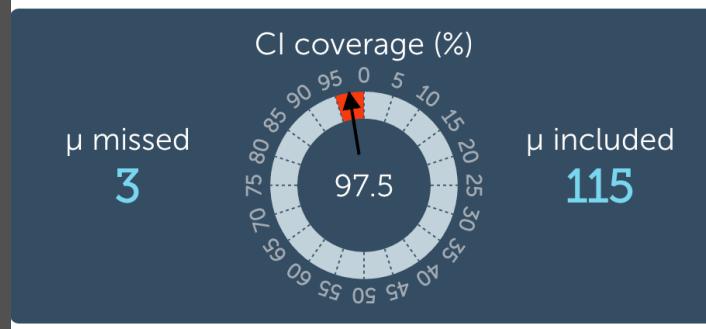
## Standard Error



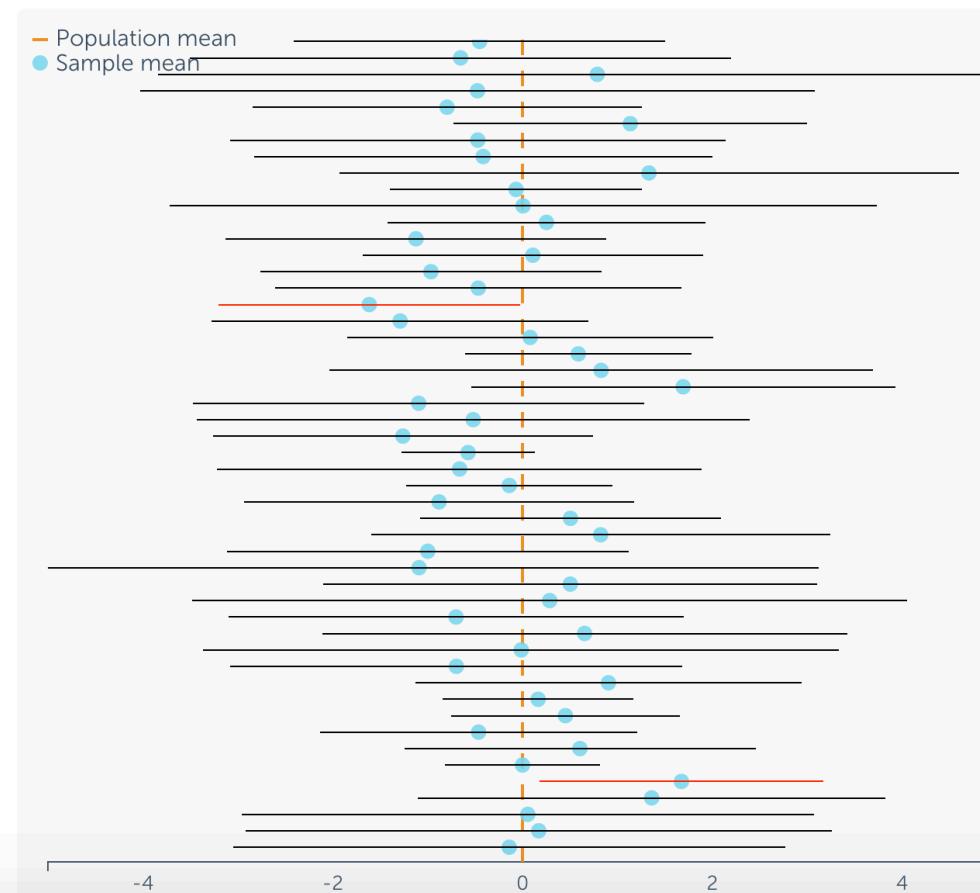
Cumming, Geoff and Finch, Sue. Inference by eye: confidence intervals and how to read pictures of data. American Psychologist, 2005.

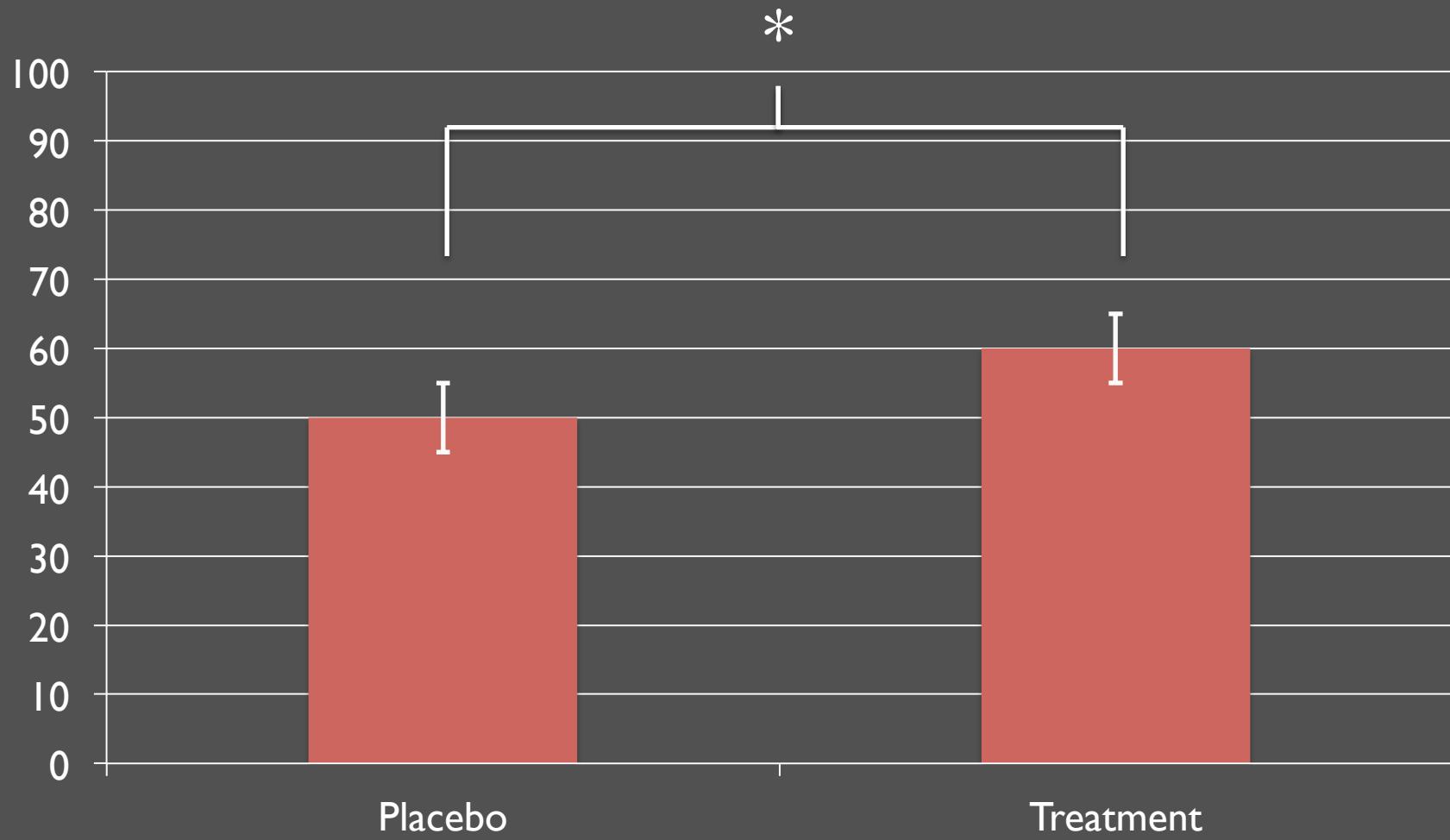
# Confidence Intervals

Simulation statistics

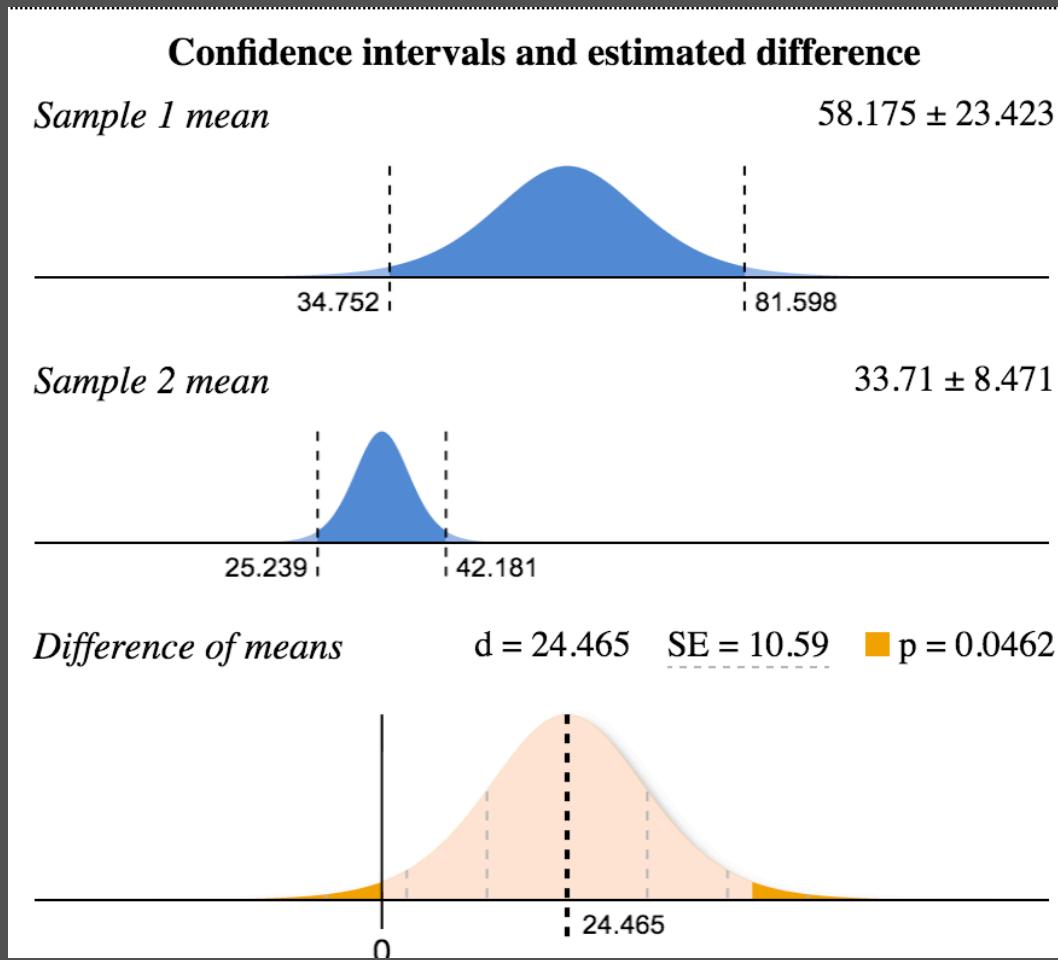


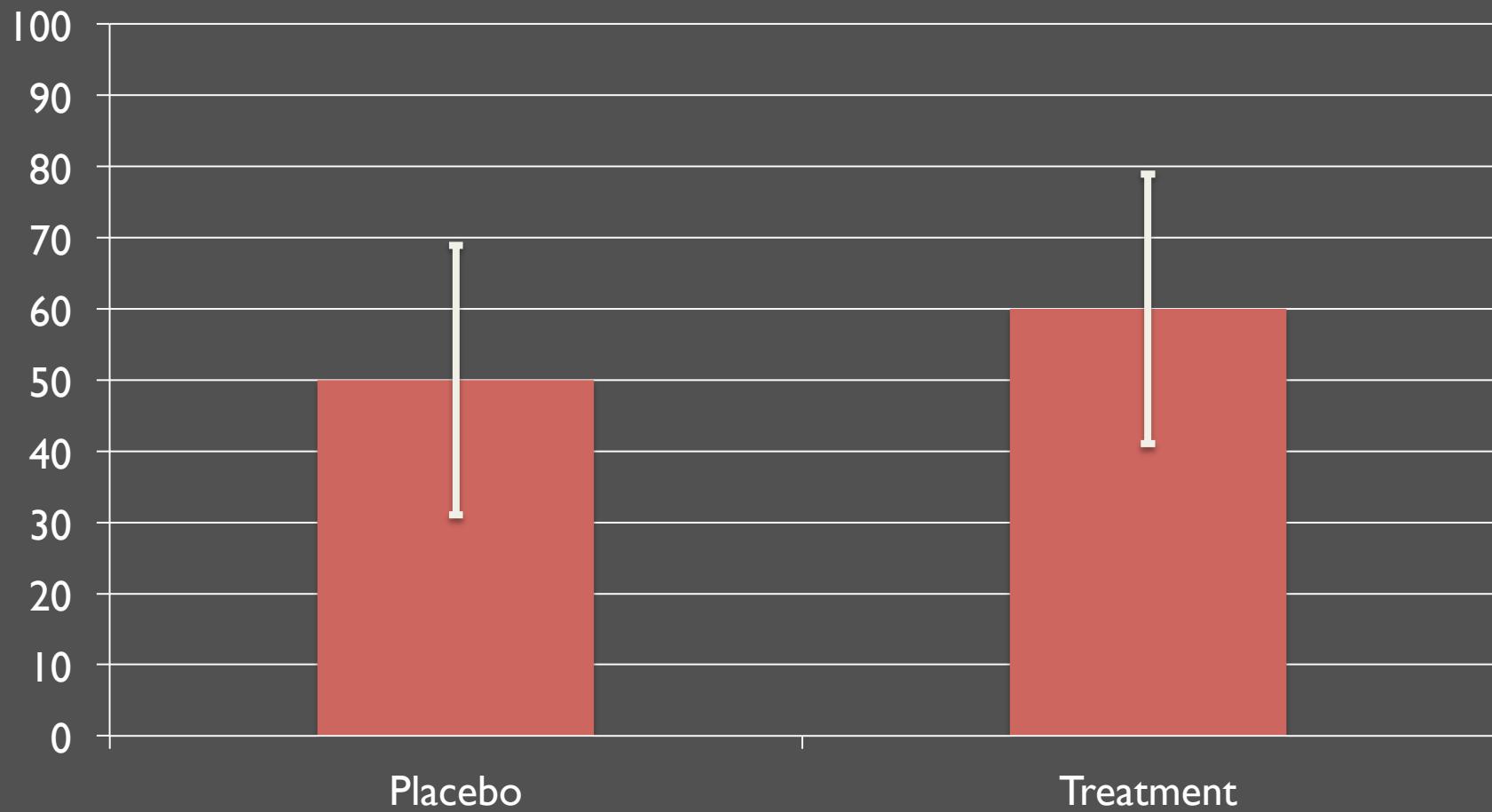
95% confidence intervals

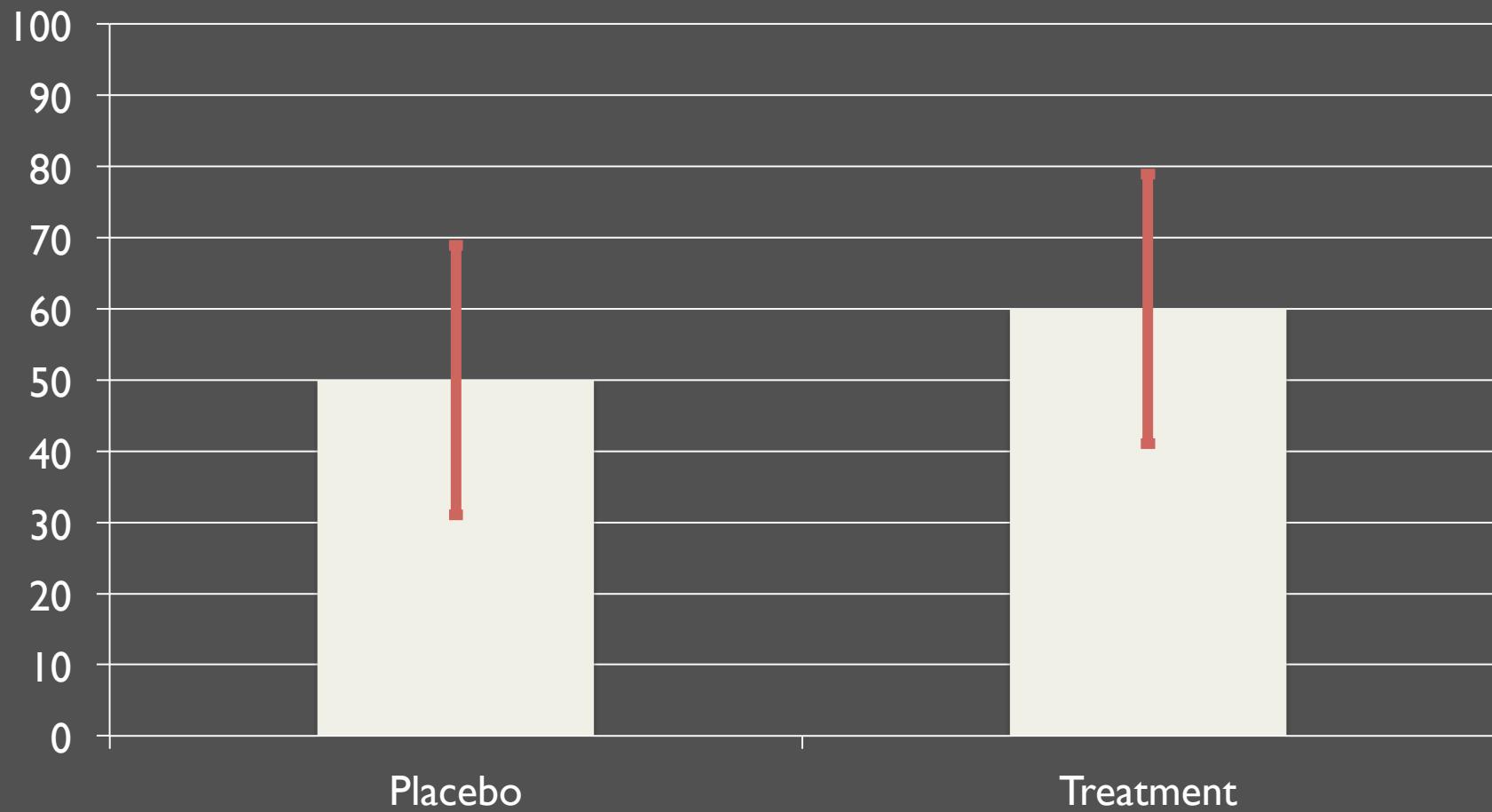




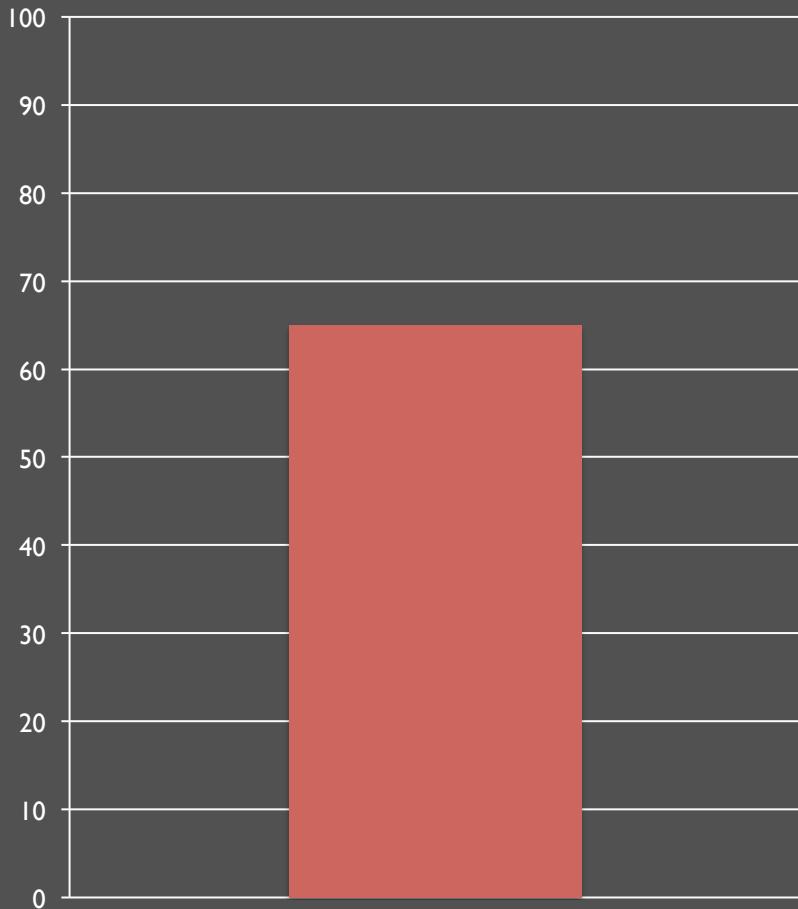
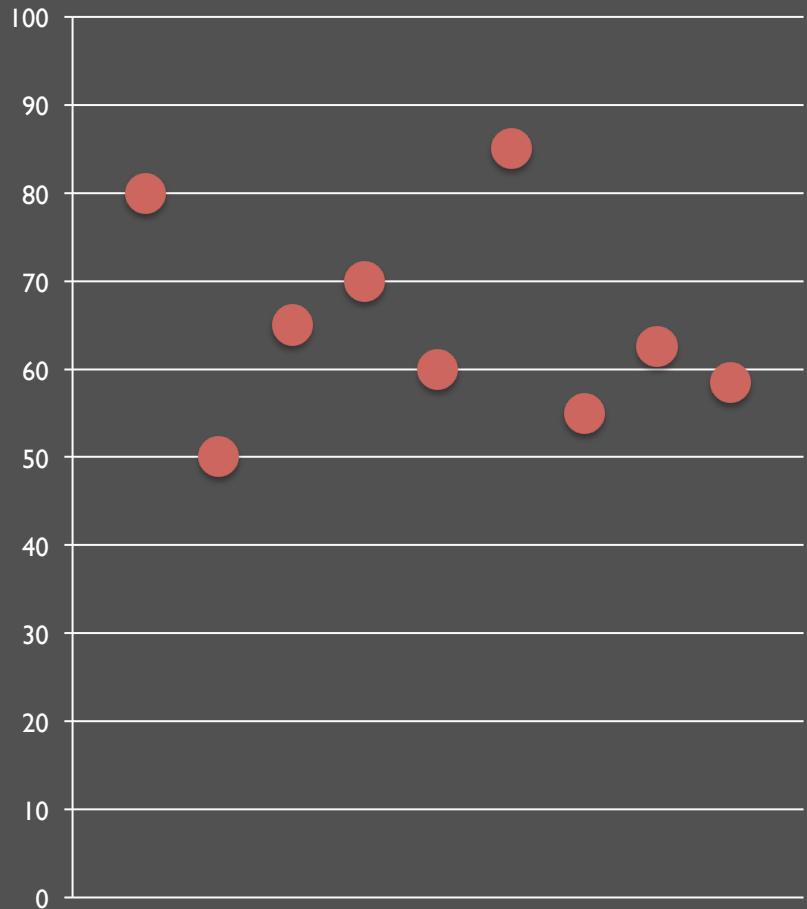
# T-Tests and Confidence Intervals





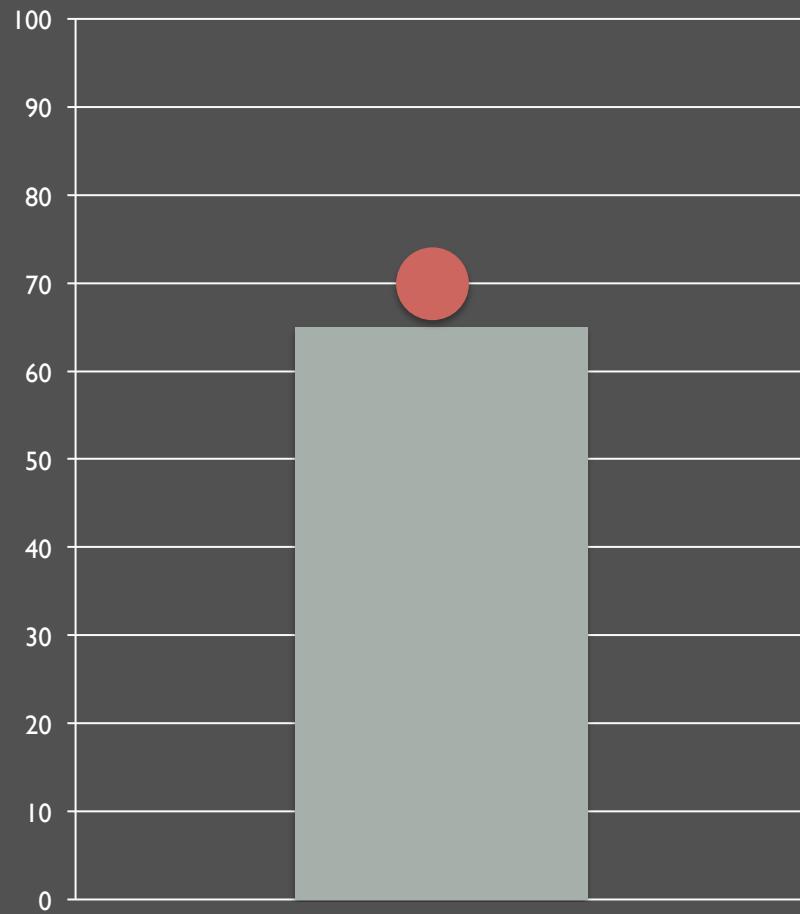


# Within-the-bar bias

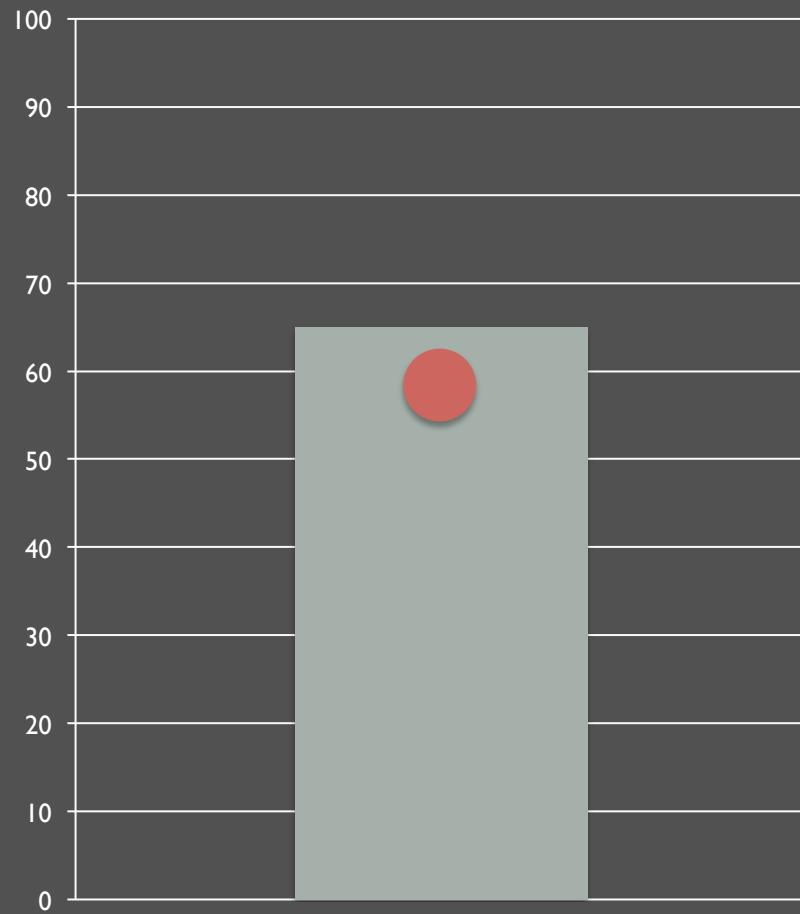
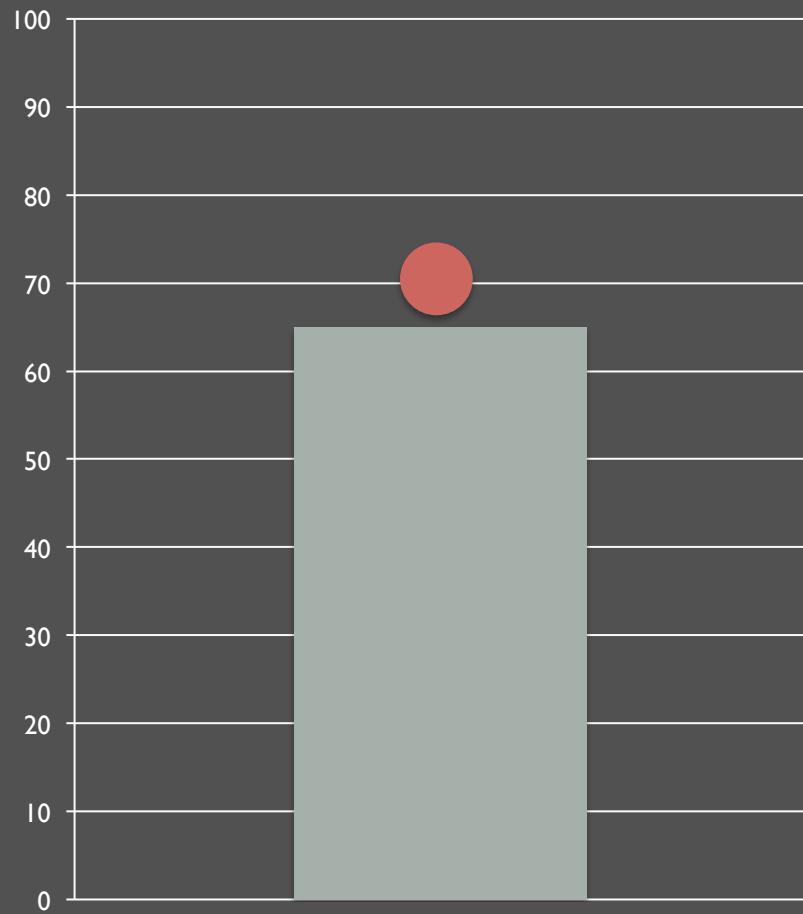


Newman, George E, and Brian J Scholl. "Bar graphs depicting averages are perceptually misinterpreted: the within-the-bar bias." *Psychonomic bulletin & review* 19.4 (2012): 601–7.

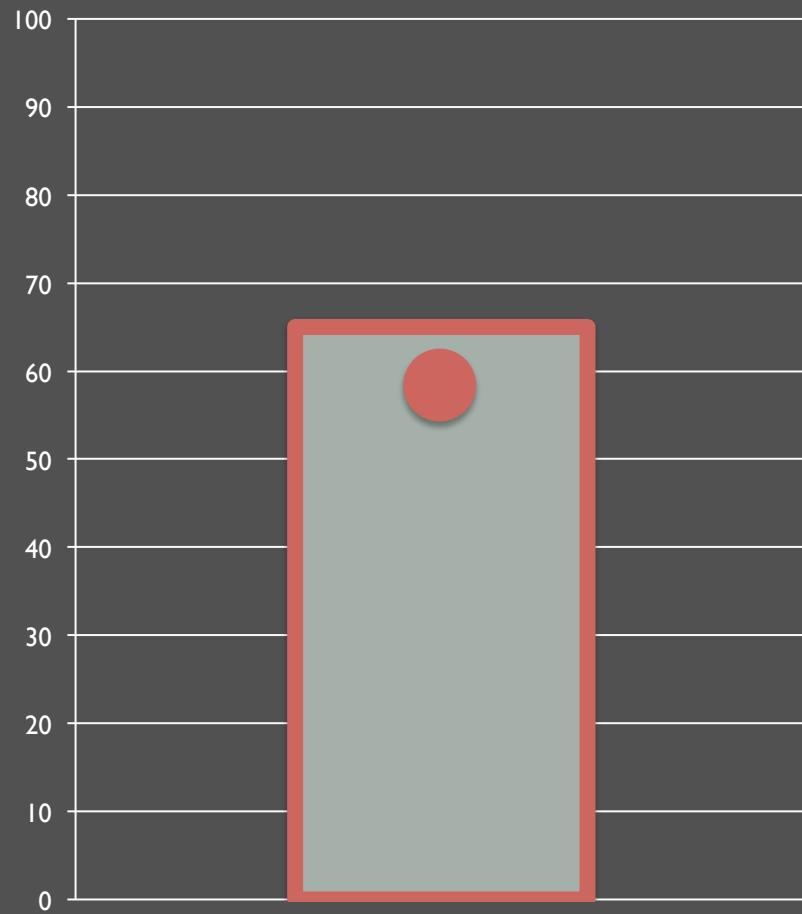
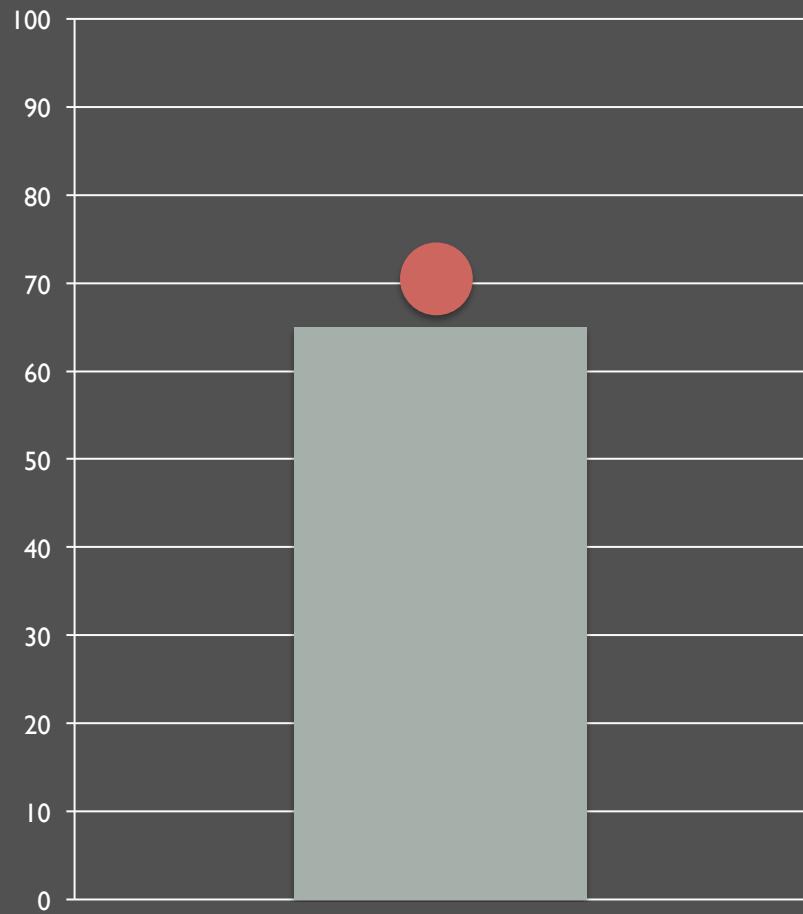
# Within-the-bar bias



# Within-the-bar bias



# Within-the-bar bias

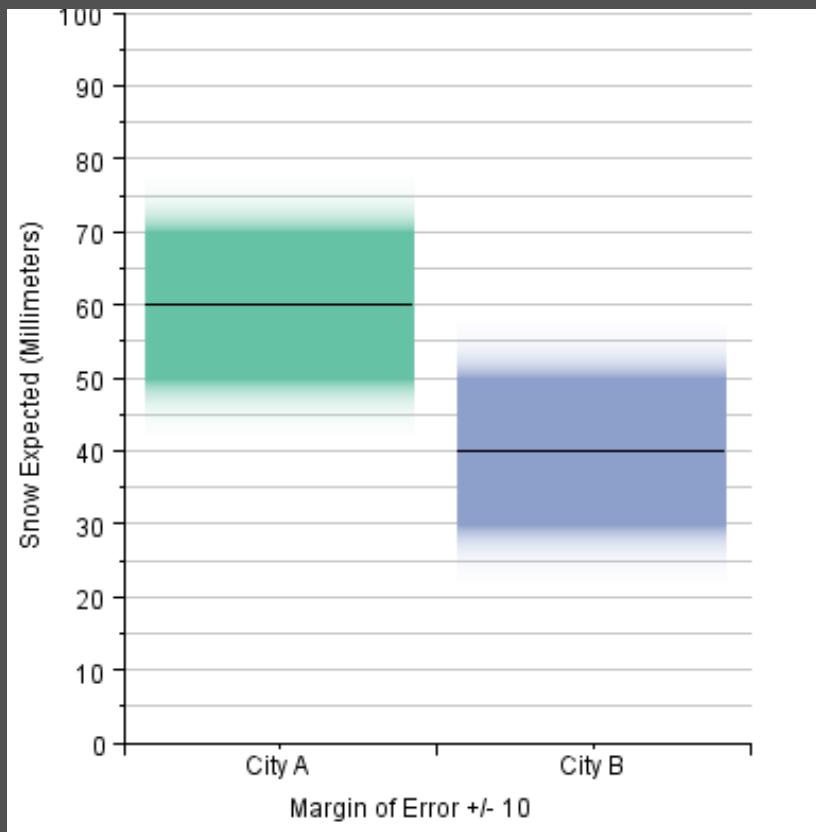


# Binary Bias

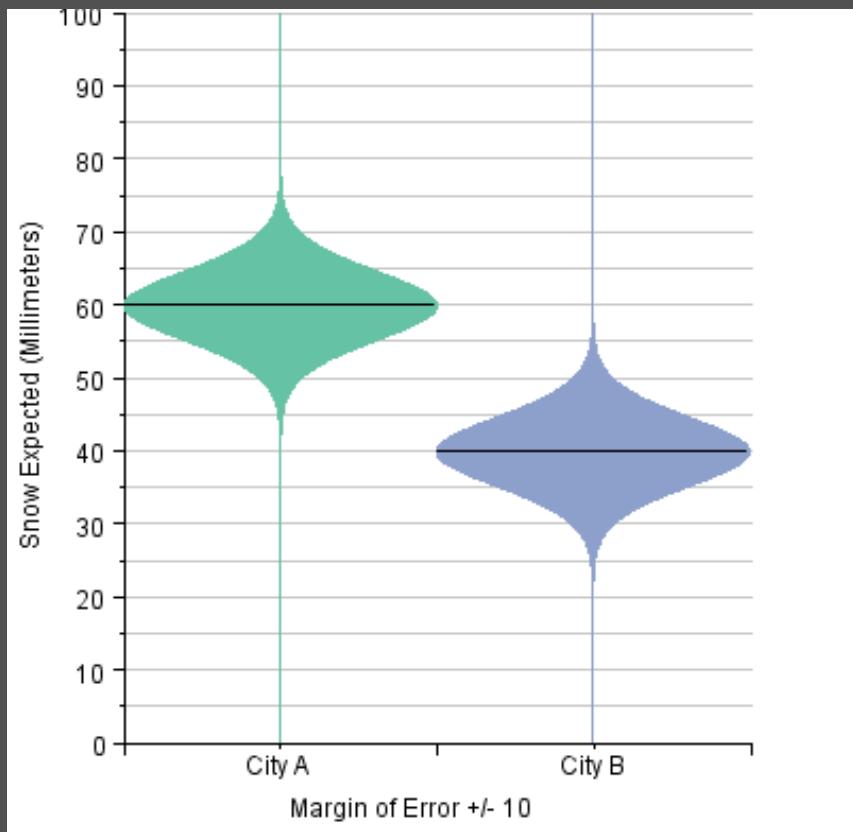


# Alternatives

**Gradient Plot**



**Violin Plot**



# Model Visualization



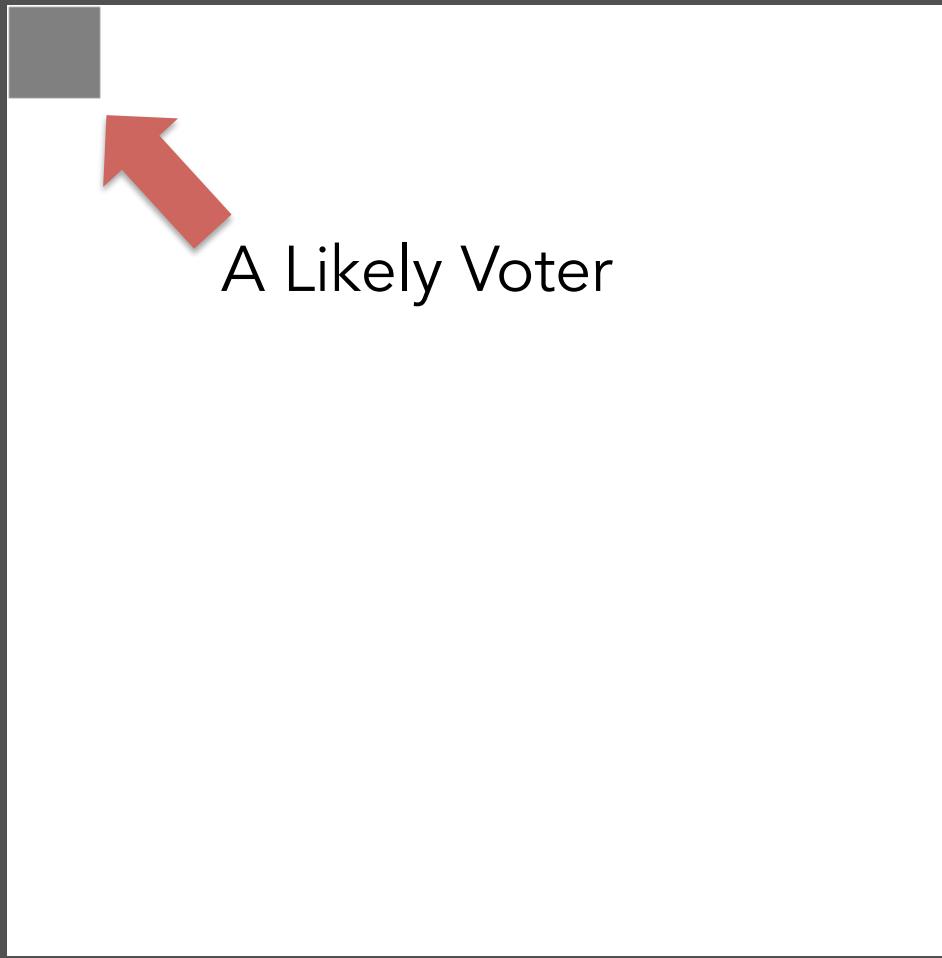
# Polling Data

Candidate A is ahead  
of Candidate B in the  
polls, with 55% of the  
likely voters\*

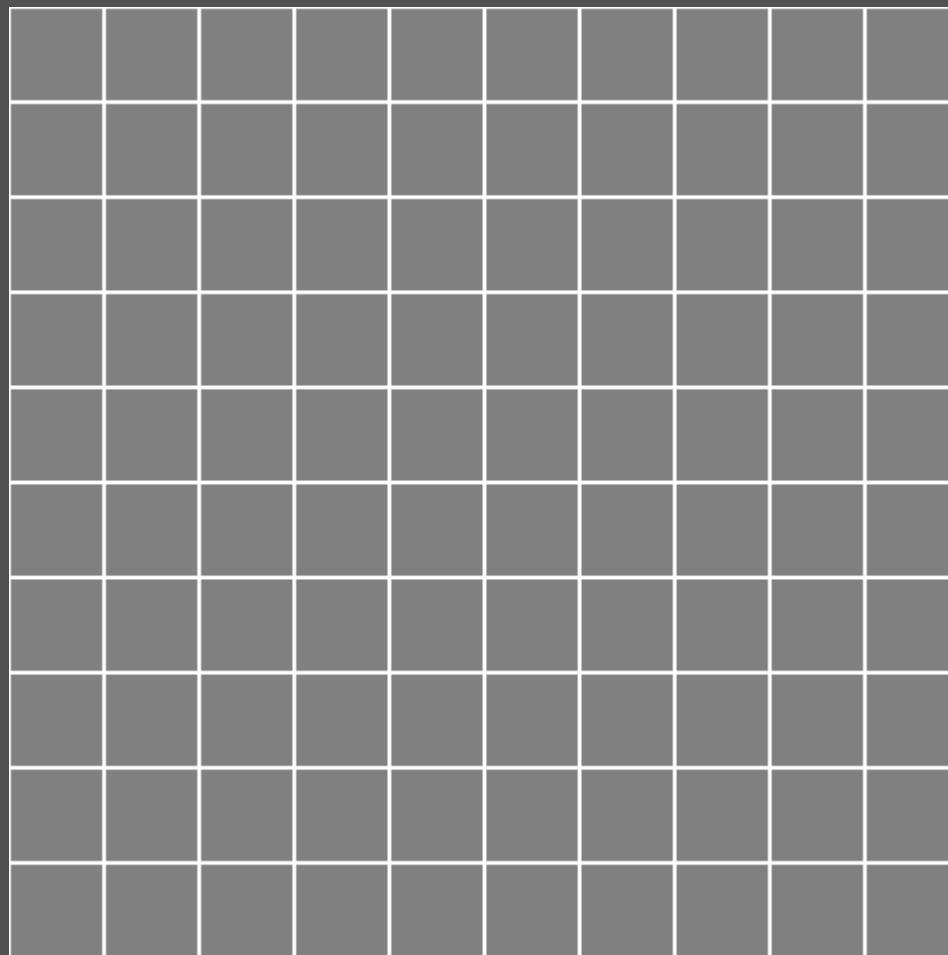
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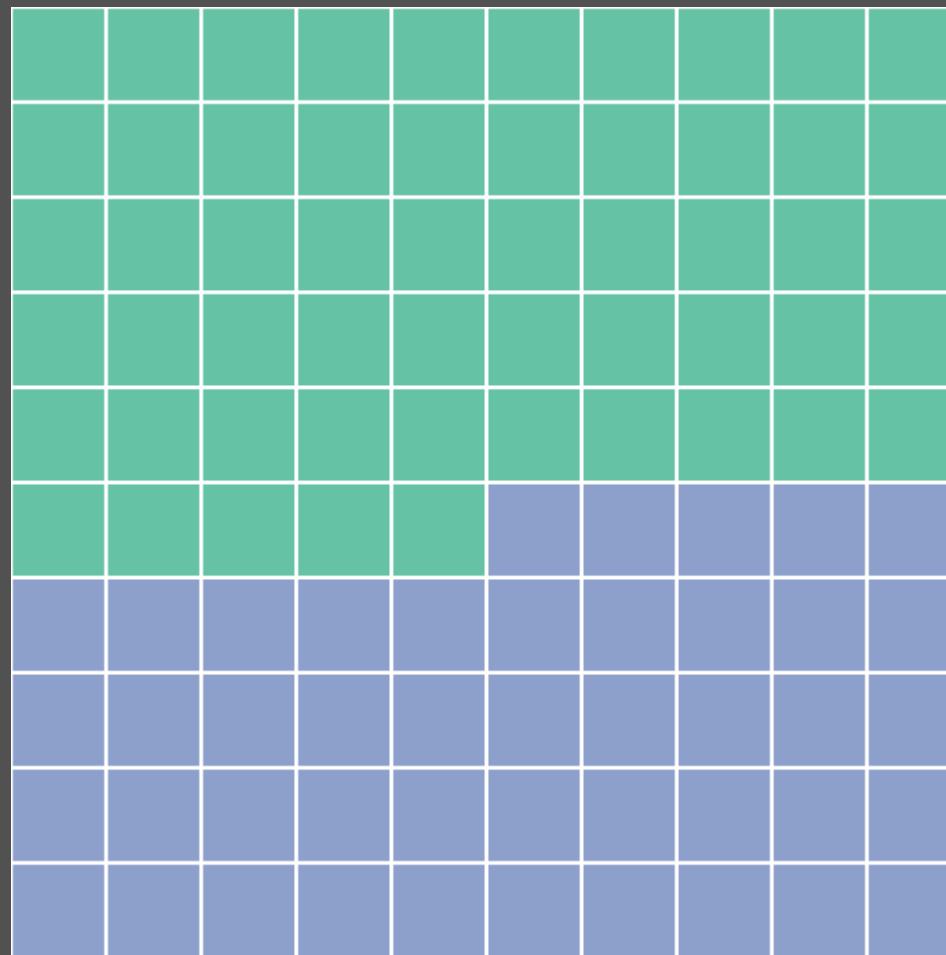
\*poll of 100 people,  
margin of error +/-5



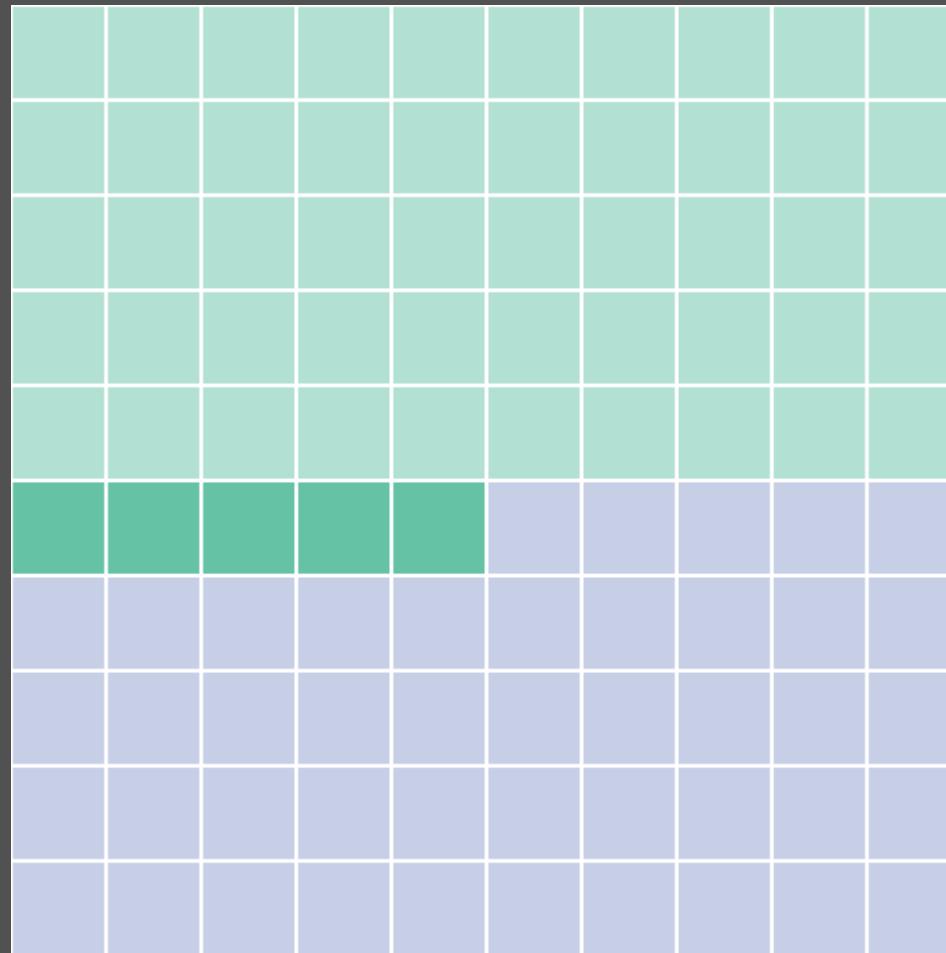
A Likely Voter



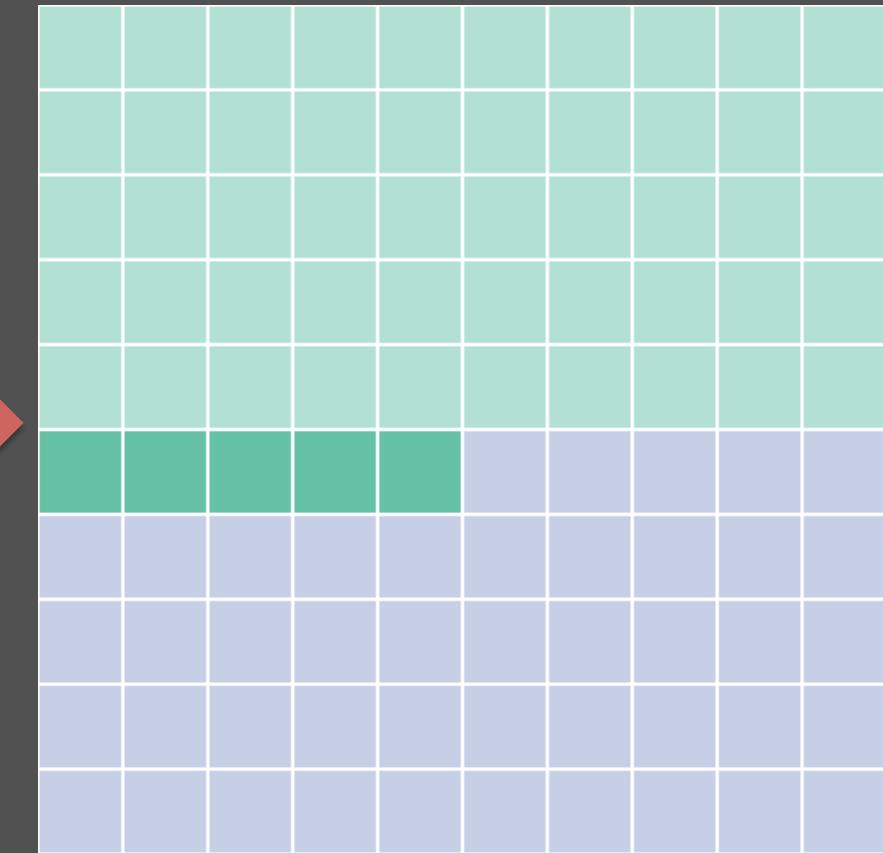
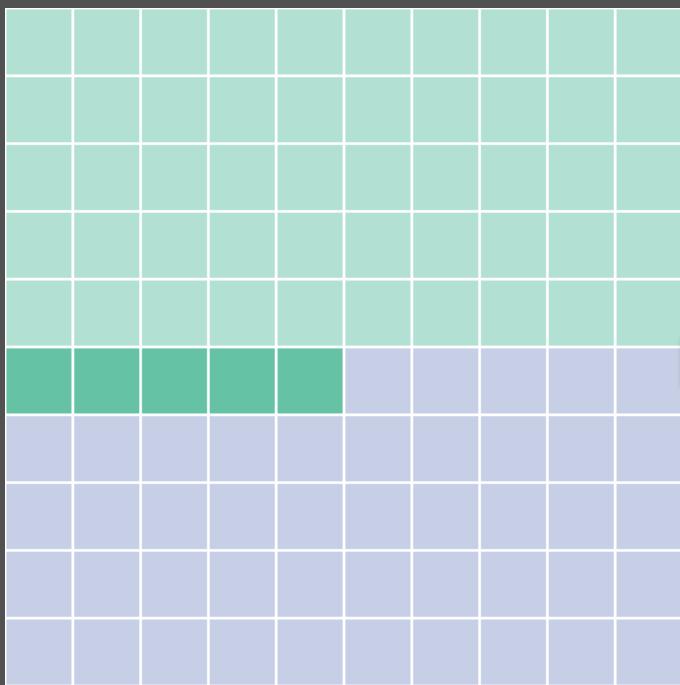
Poli



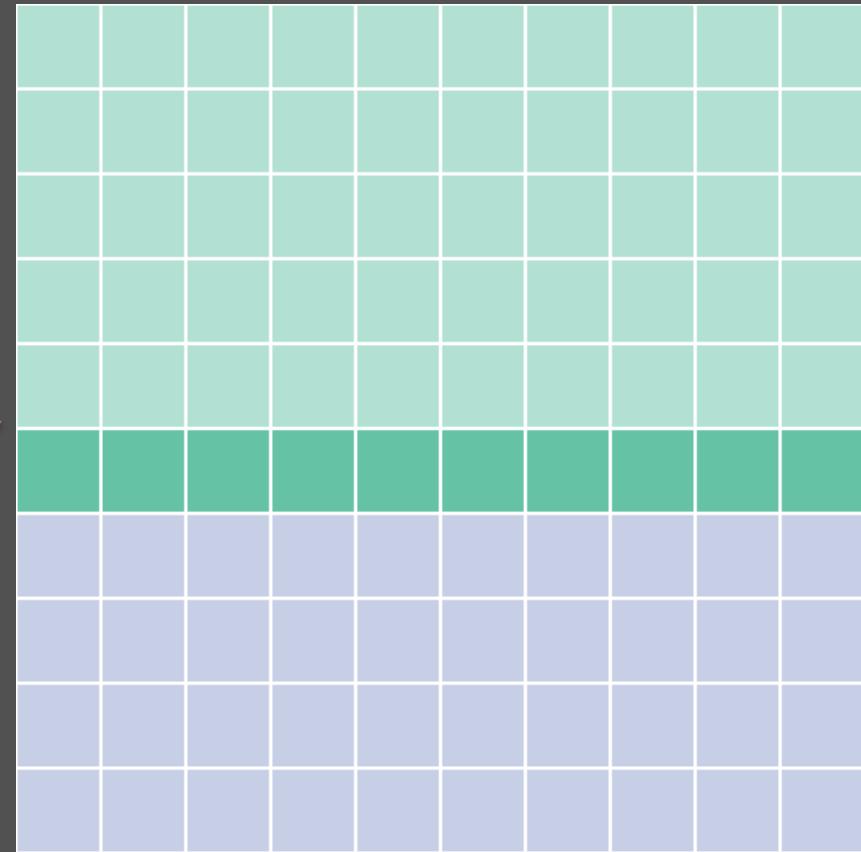
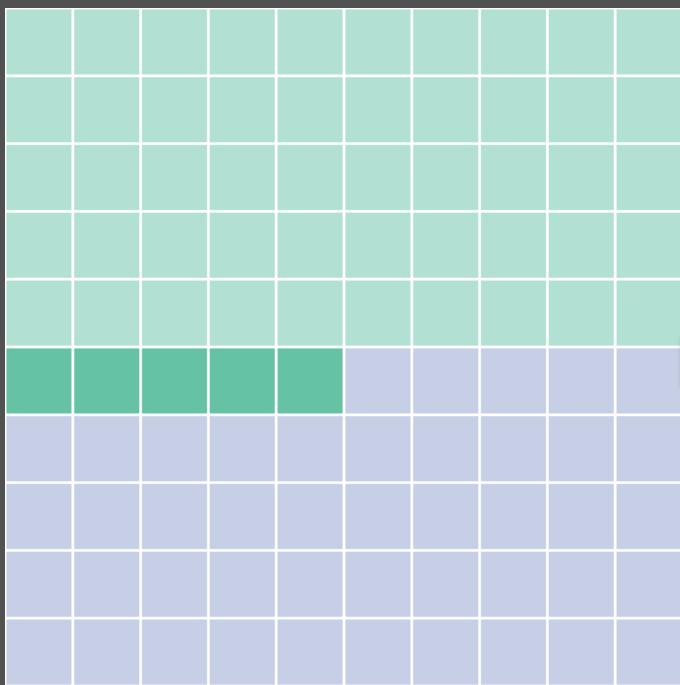
Poli



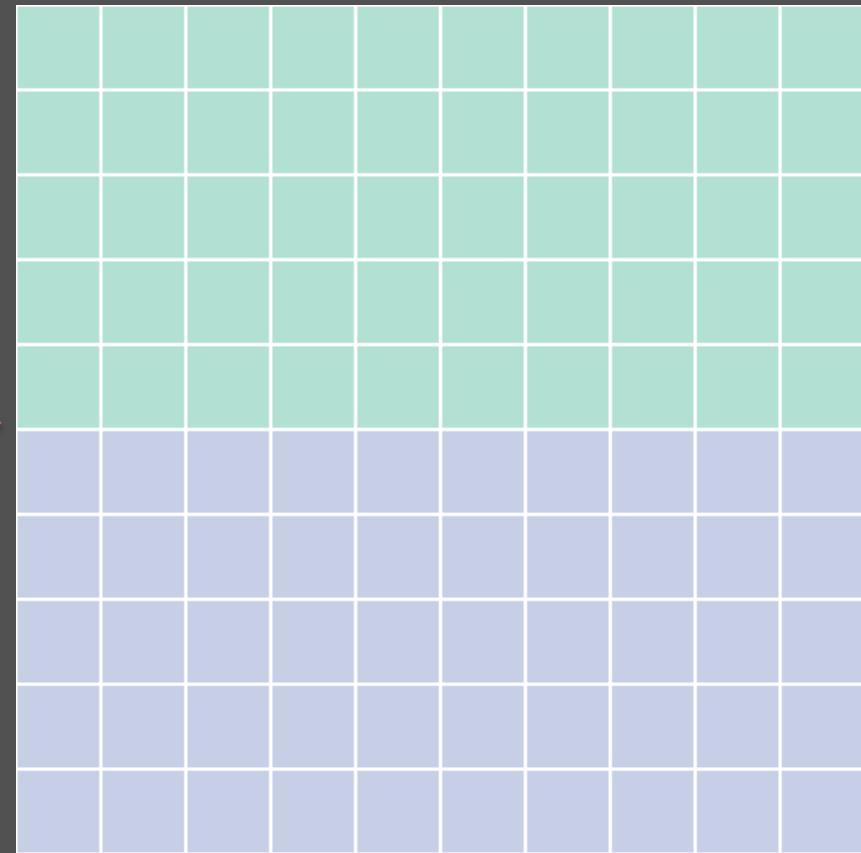
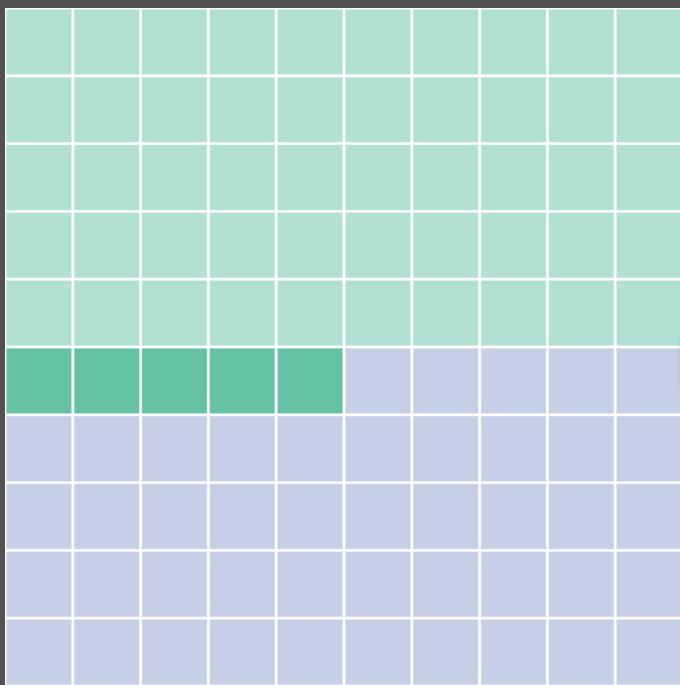
# Actual Election?



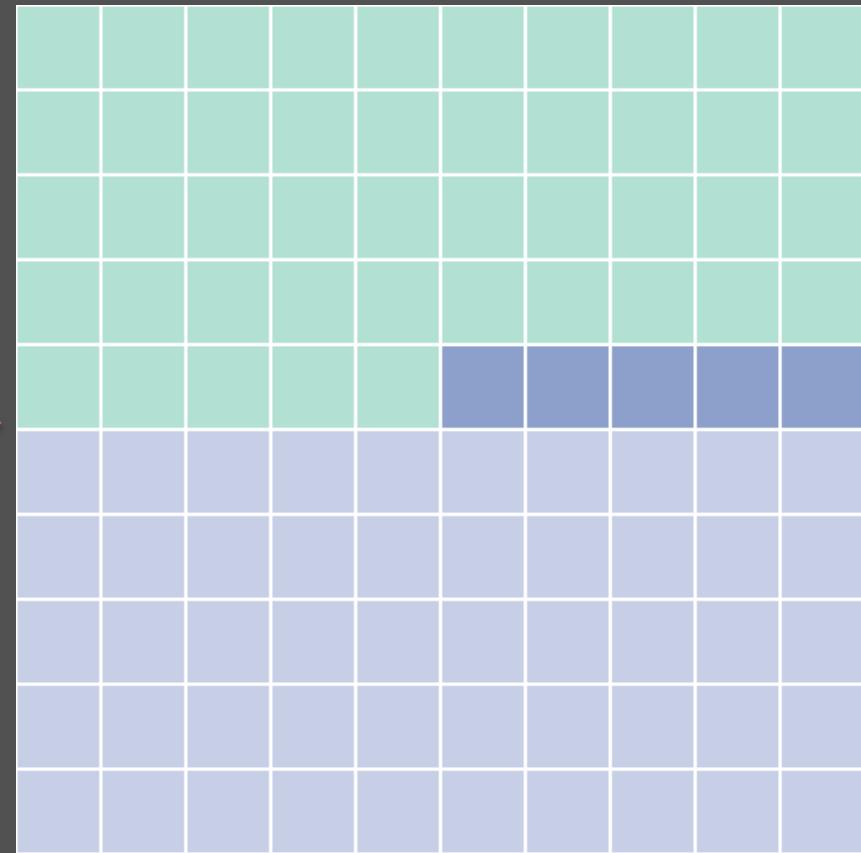
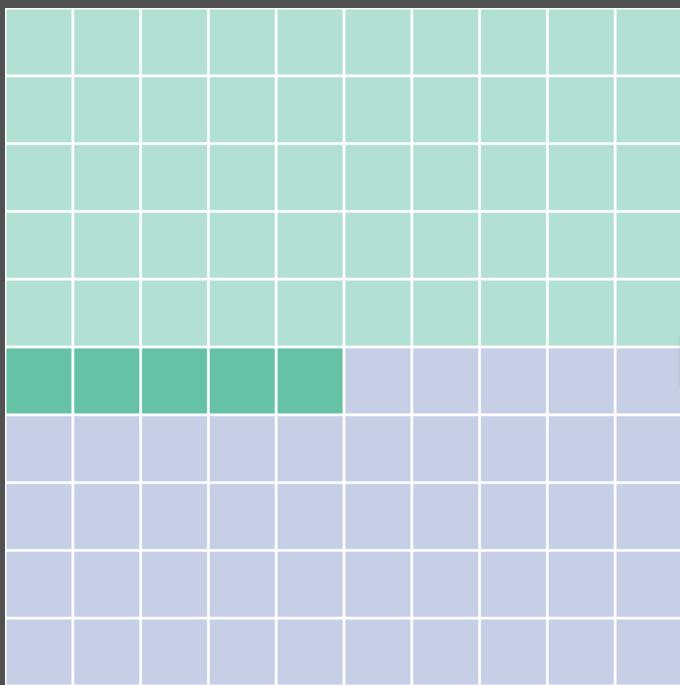
# Actual Election?

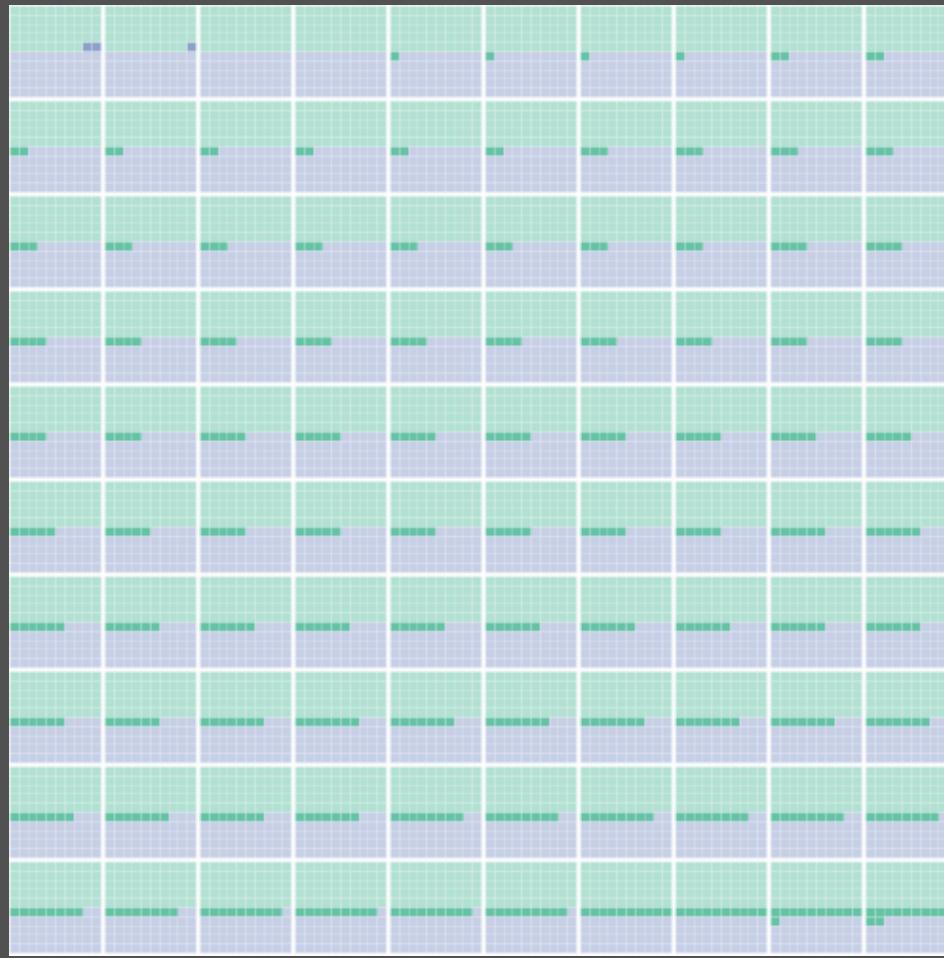


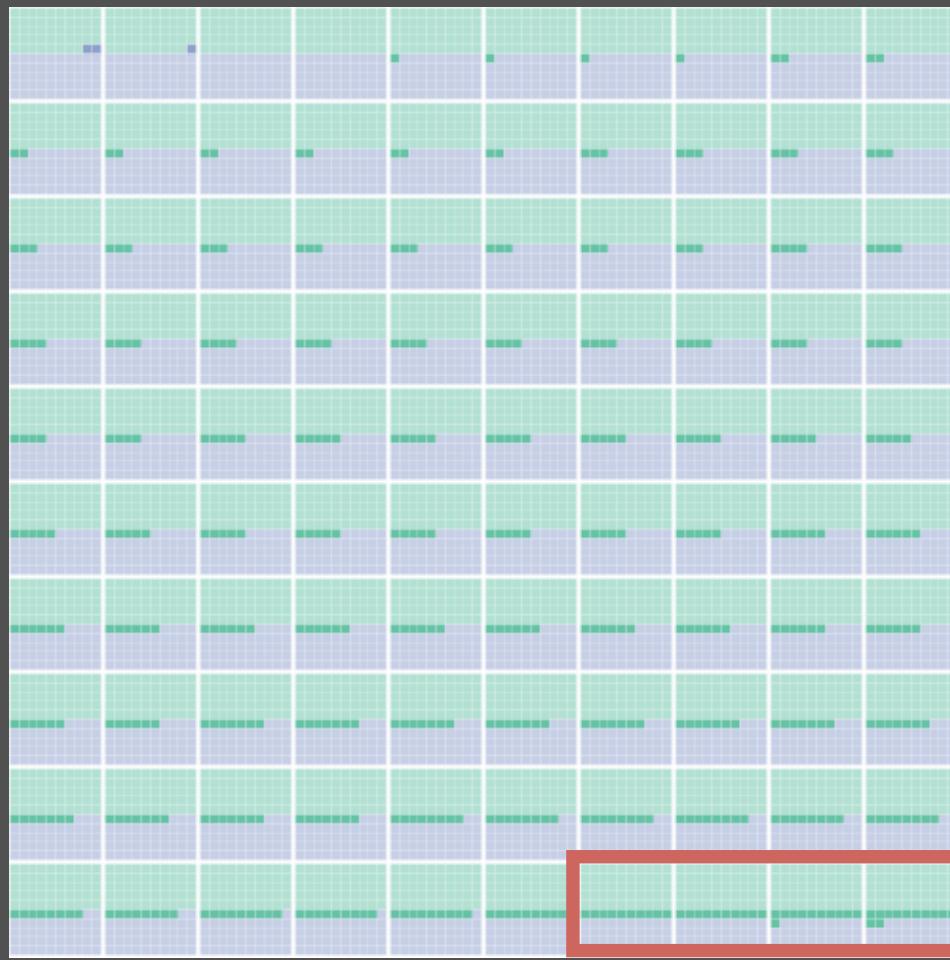
# Actual Election?

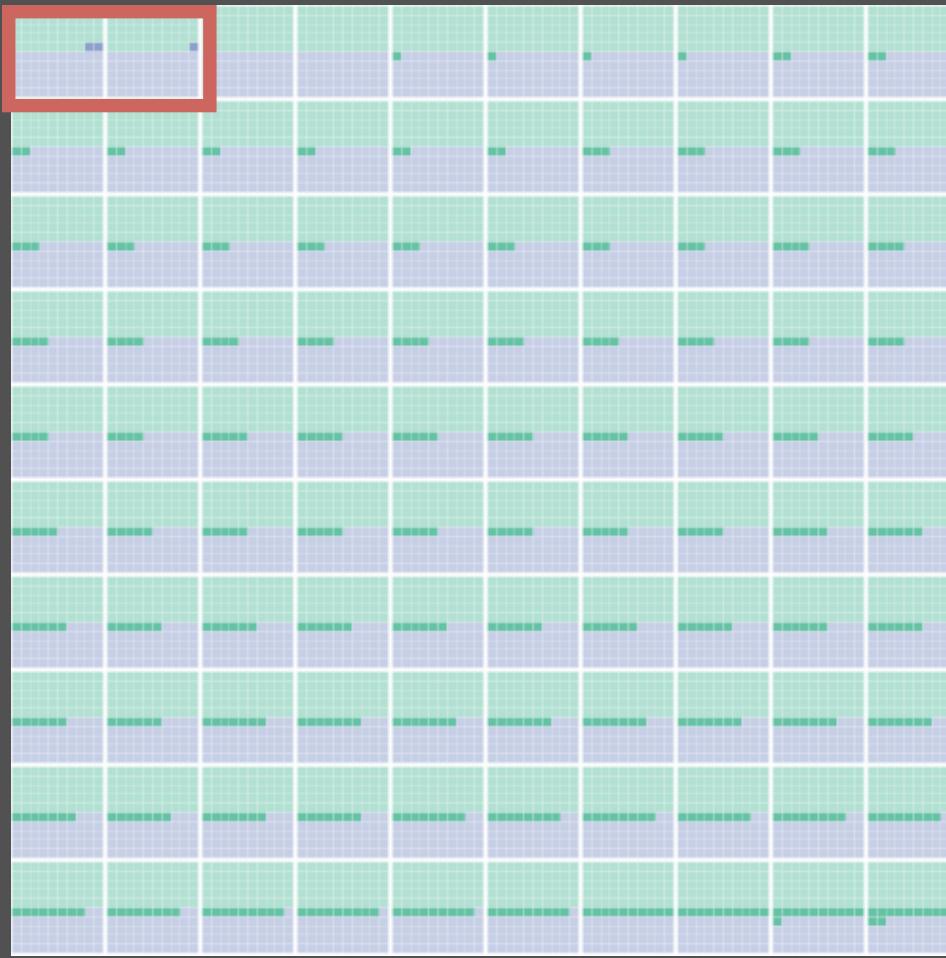


# Actual Election?





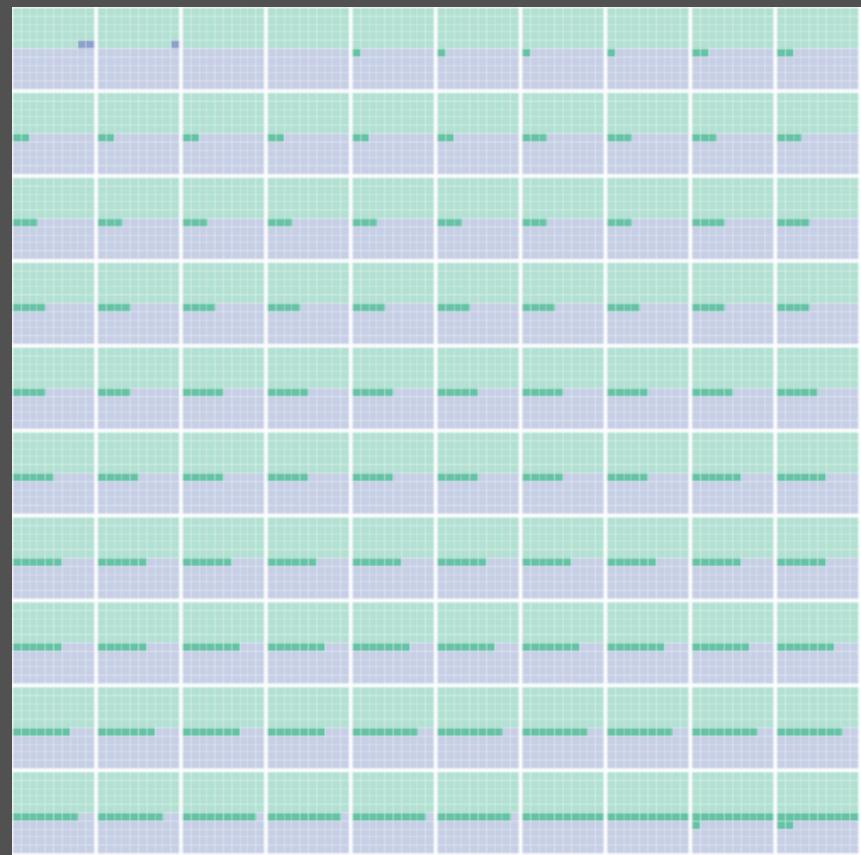




# Pangloss Plot

Candidate A is ahead of Candidate B in the polls, with 55% of the likely voters\*

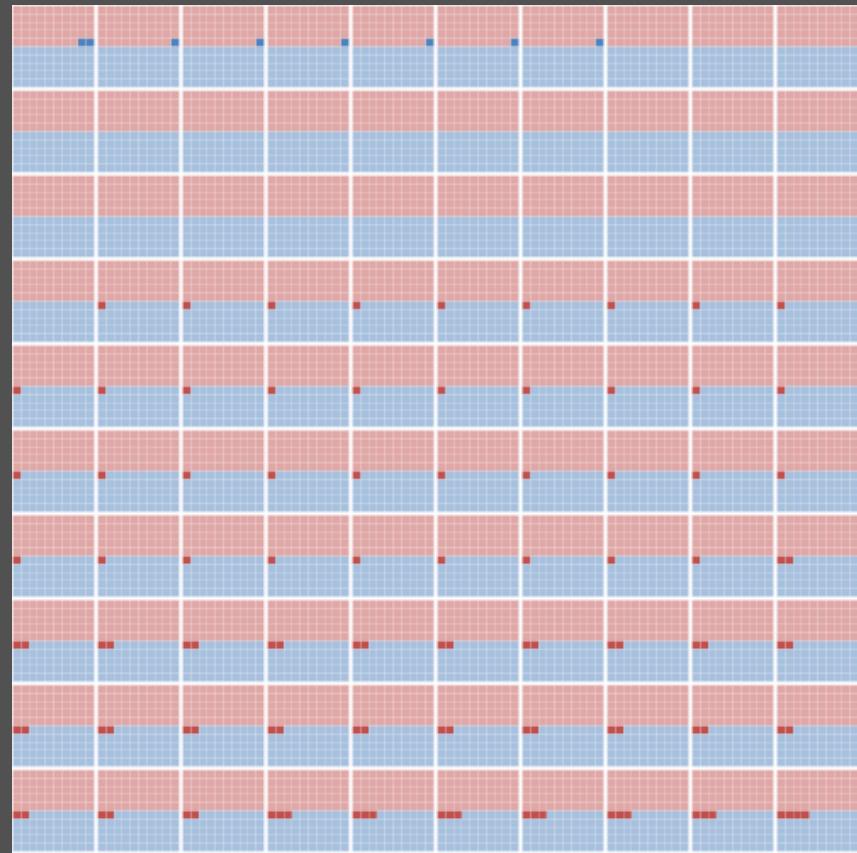
\*poll of 100 people,  
margin of error +/-5



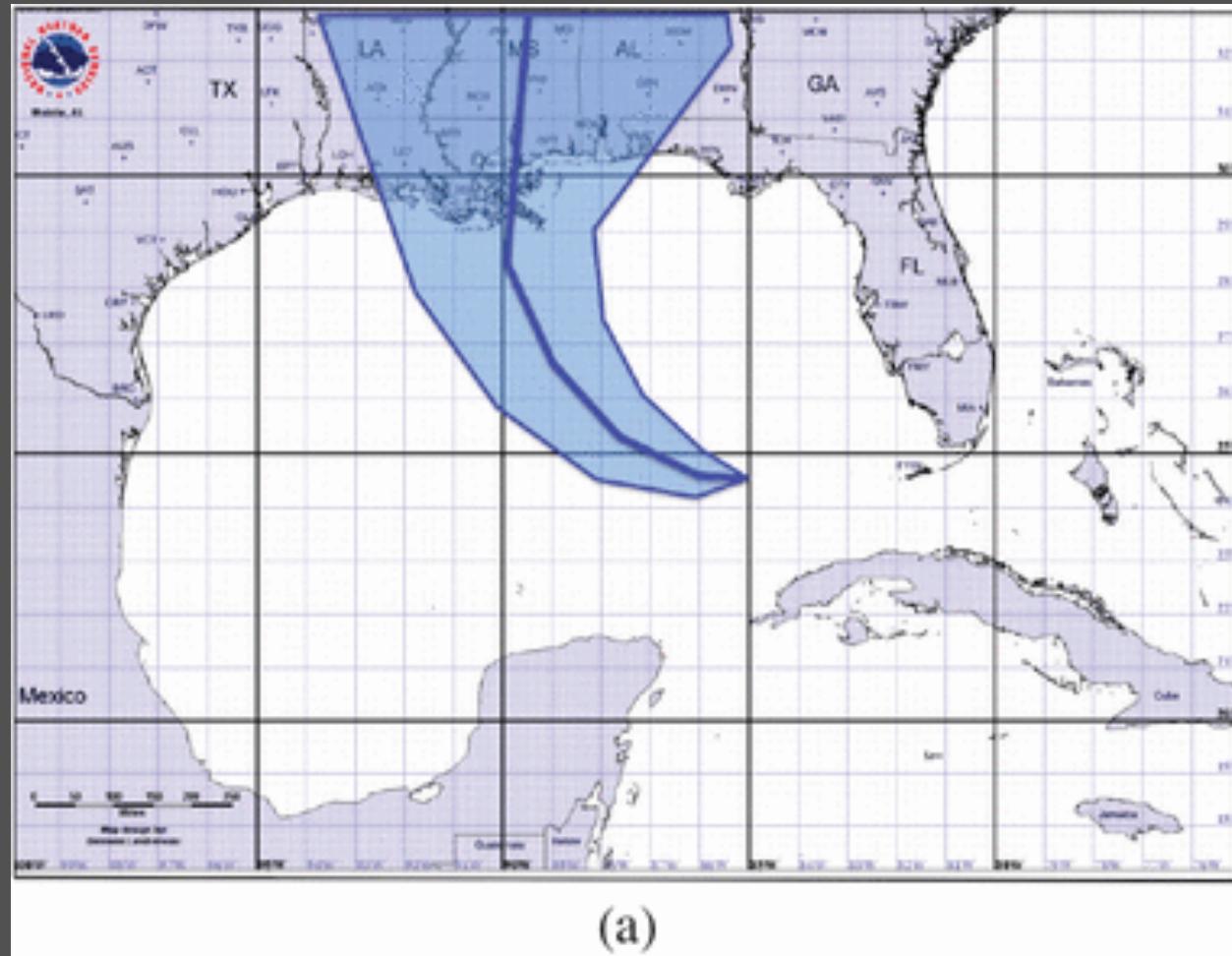
# Pangloss Plot

Romney is ahead of Obama in the polls, with 51% of the likely voters\*

\*poll of 3,117 people, margin of error +/-2

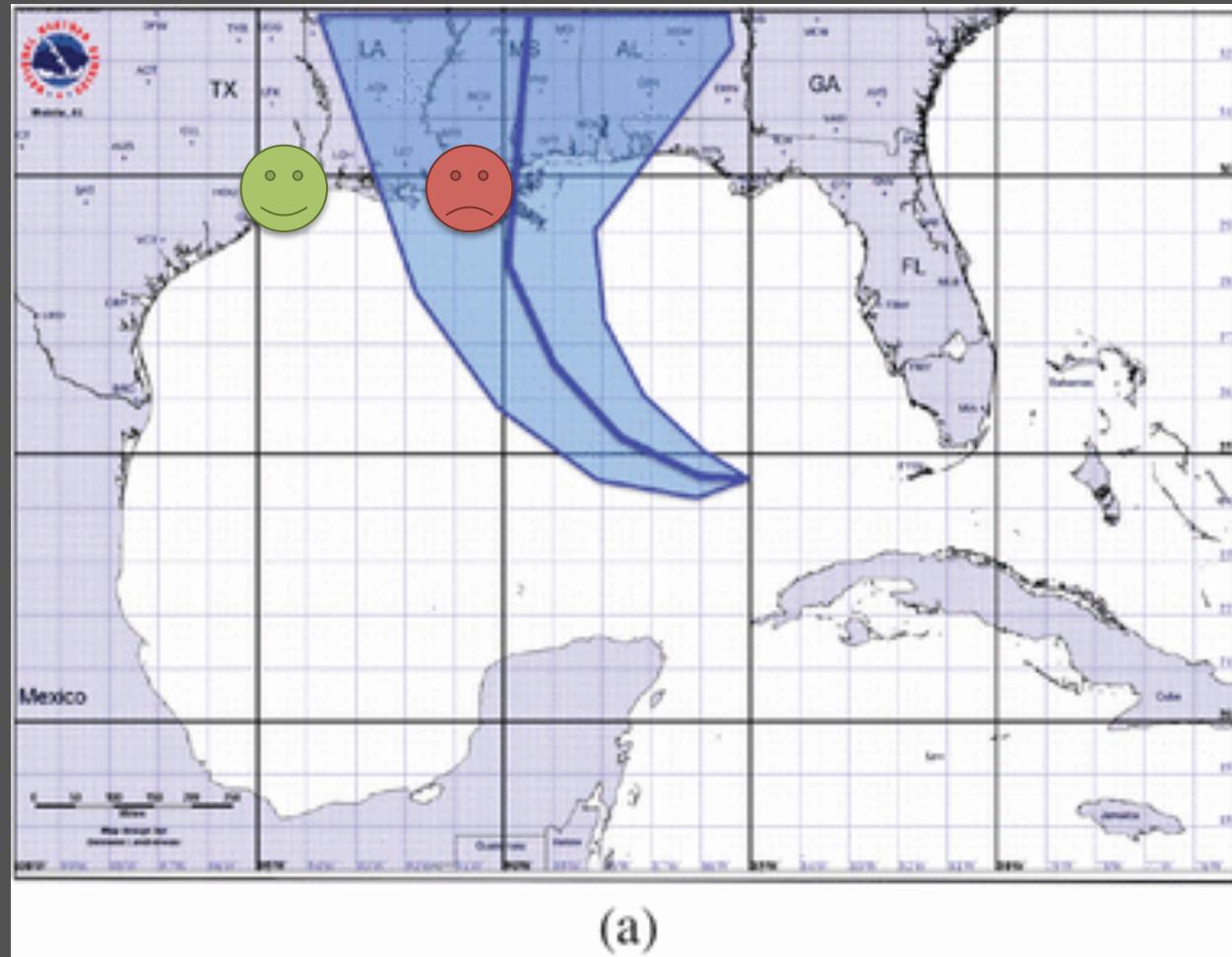


# Model Visualization



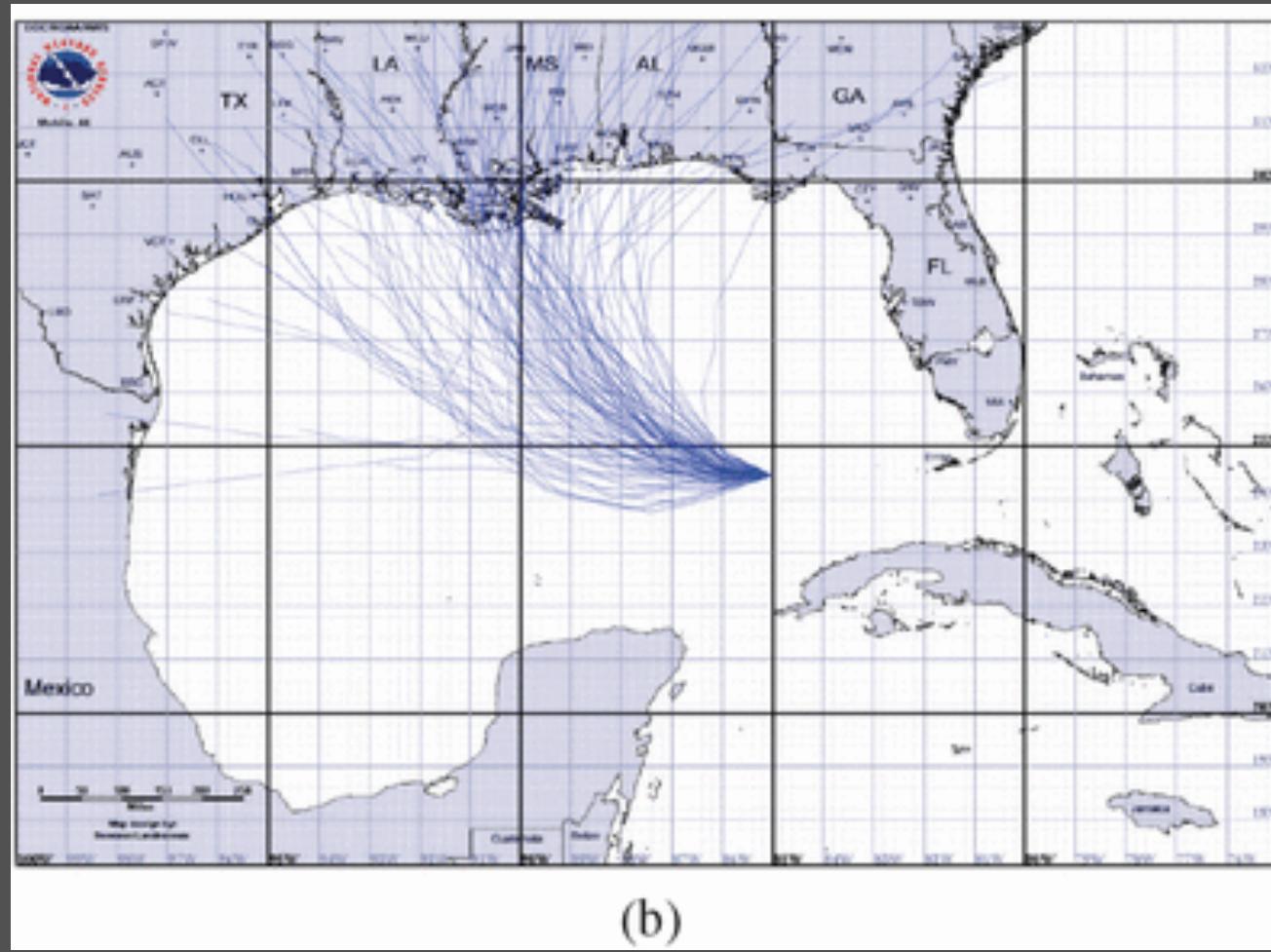
Cox, Jonathan and House, Donald and Lindell, Michael. Visualising uncertainty in predicted hurricane tracks. International Journal for Uncertainty Quantification, 2013.

# Model Visualization

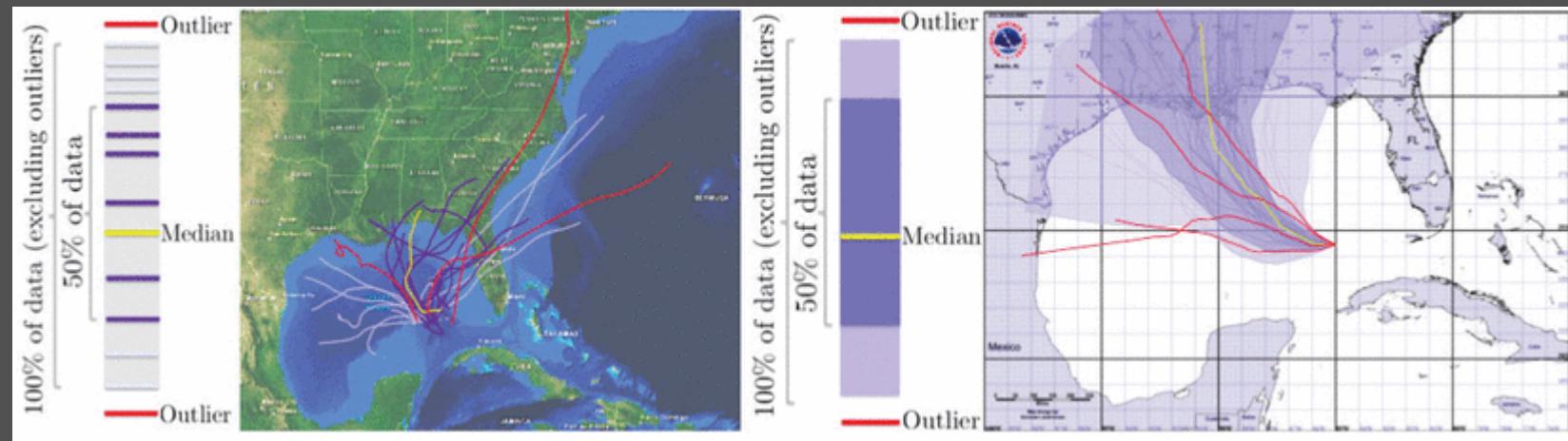


Cox, Jonathan and House, Donald and Lindell, Michael. Visualising uncertainty in predicted hurricane tracks. International Journal for Uncertainty Quantification, 2013.

# Model Visualization

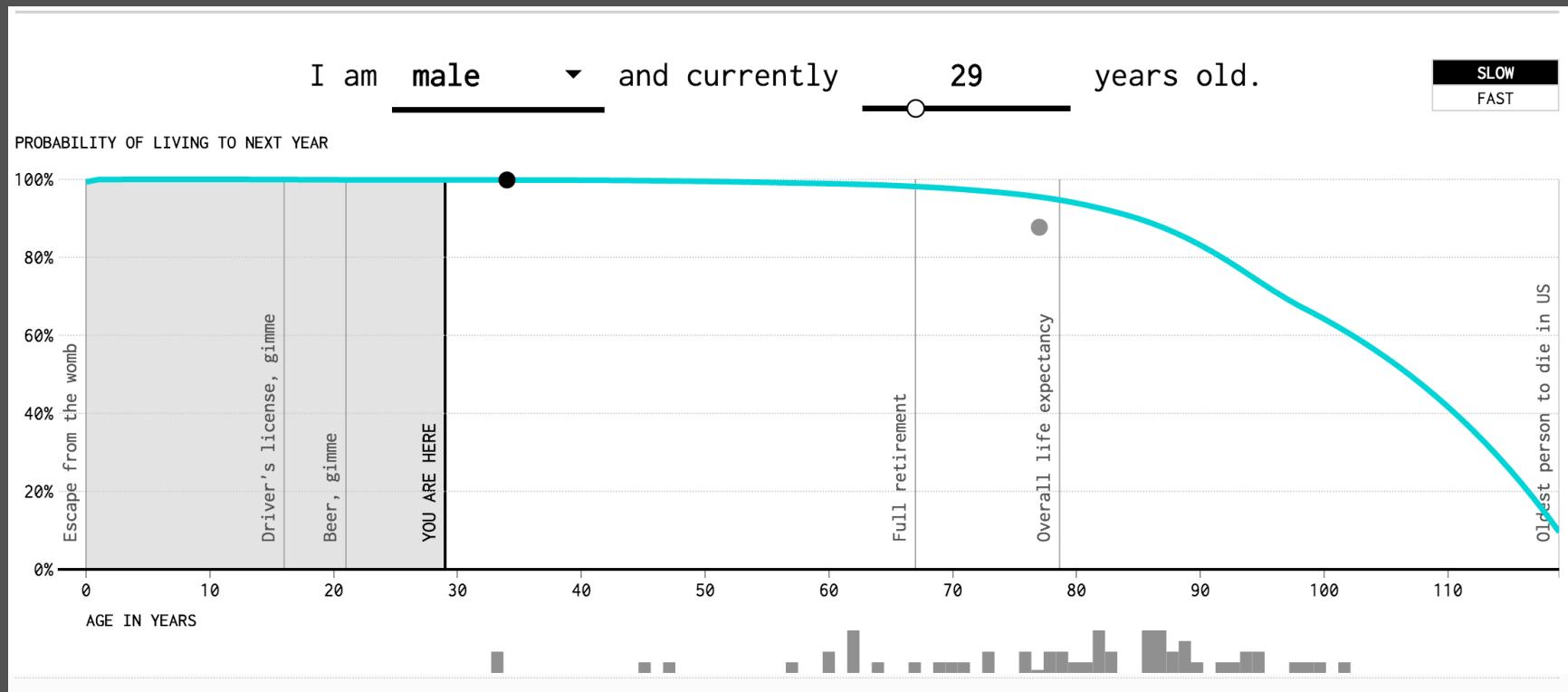


# Model Visualization

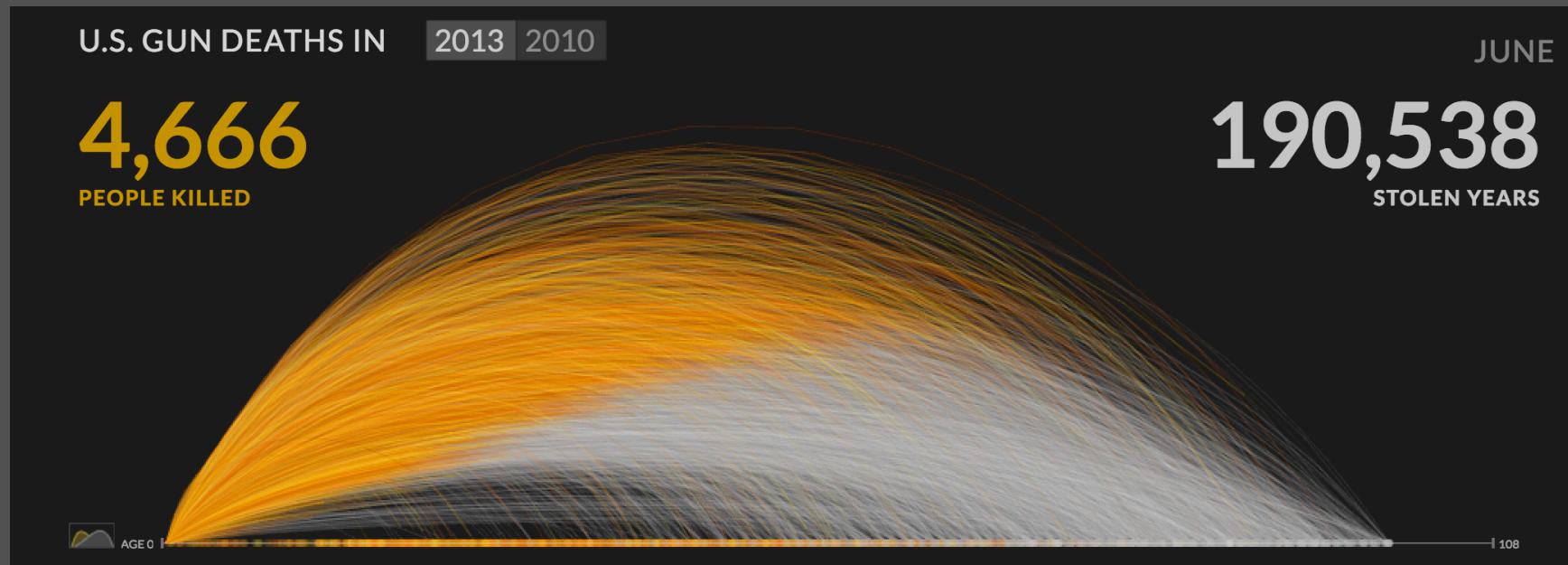


M. Mirzargar, R. Whitaker and R. Kirby. Curve Boxplot: Generalization of Boxplot for Ensembles of Curves. IEEE VIS 2014.

# Life Expectancy



# Gun Deaths



# Model Visualization

Building models is necessary to quantify uncertainty

It is important to communicate the variability in model outcomes

Dynamic displays can help communicate complex models

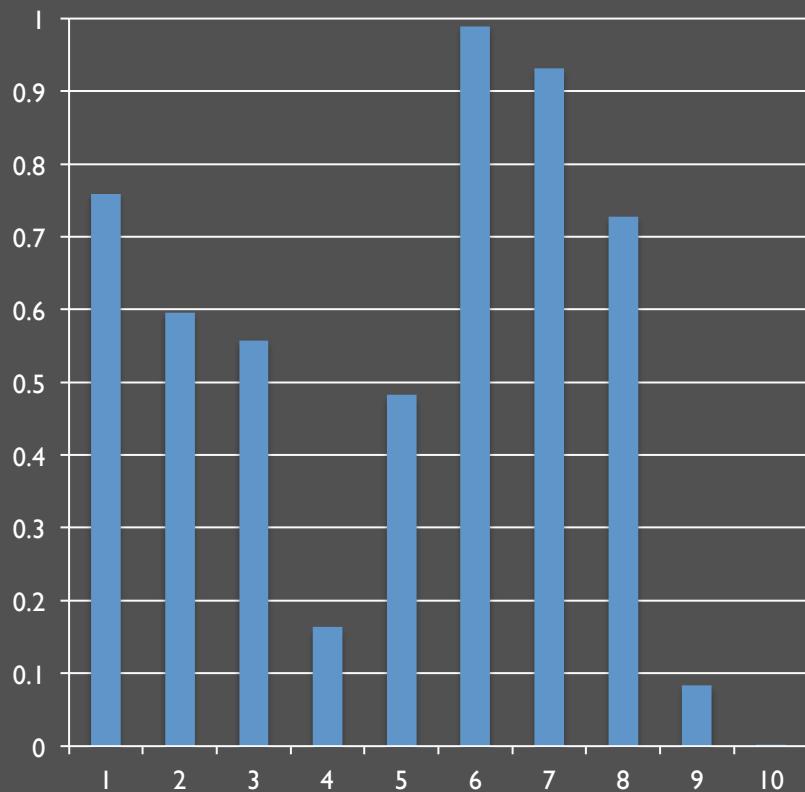
# Cognitive Biases

THINKING,  
FAST AND SLOW

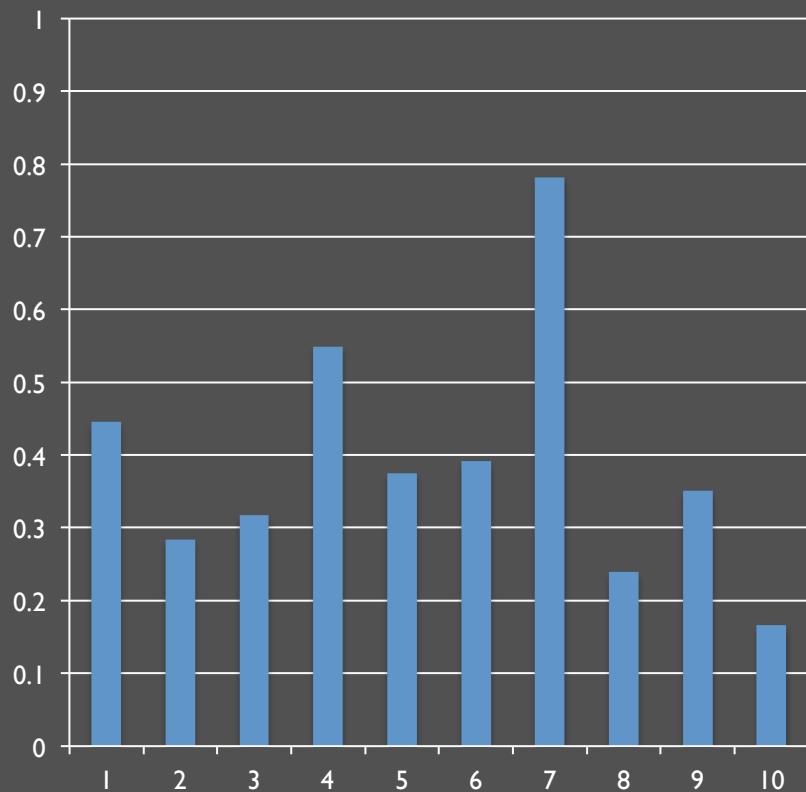


# Which Stock To Buy?

**Company A**

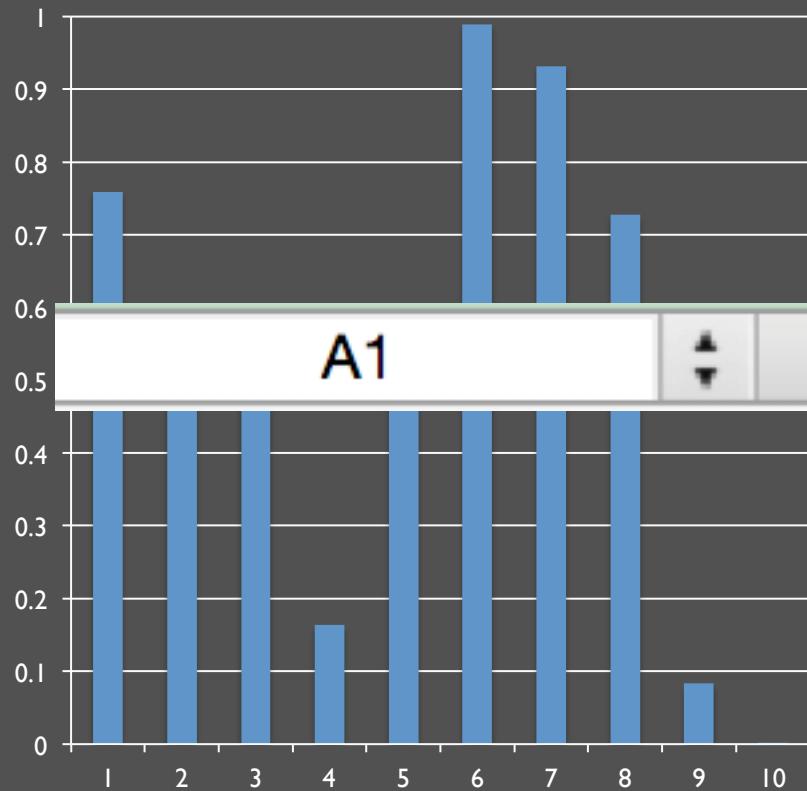


**Company B**

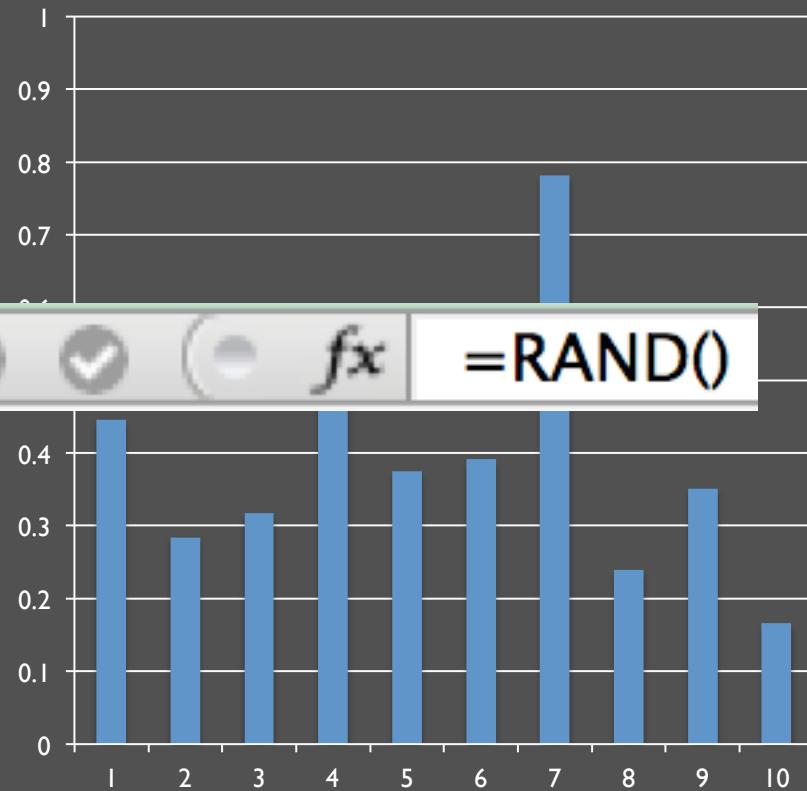


# Neither!

Company A



Company B



Wu Wei

無為

# Pareidolia



# Jobs Reports

If the economy actually added 150,000 jobs last month, it would be possible to see any of these headlines:

The jobs number is just an estimate, and it comes with uncertainty.

*Job Growth Plummets Amid Prospect Of New Slump*

*Disappointing Jobs Report Raises Economic Worries*

*Slower Job Creation Disappoints Economists*

*Job Growth Steady, New Report Says*

*Job Creation Accelerates In Sign Of Economy Improving*

*Job Growth Robust, Pointing To Economy Surging*

Under 55,000 jobs

4% chance

55,000 to 110,000

19% chance

110,000 to 140,000

19% chance

160,000 to 190,000

19% chance

190,000 to 245,000

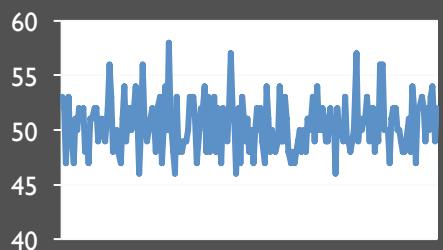
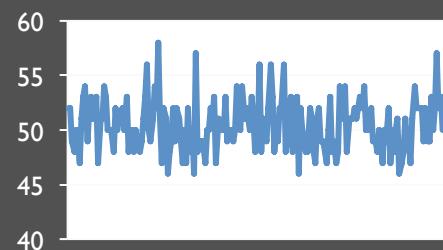
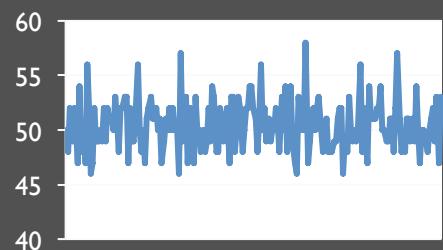
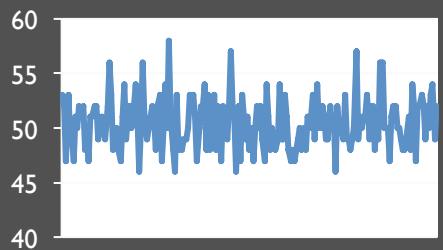
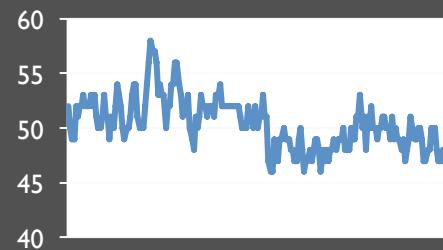
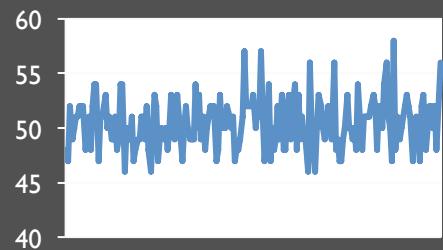
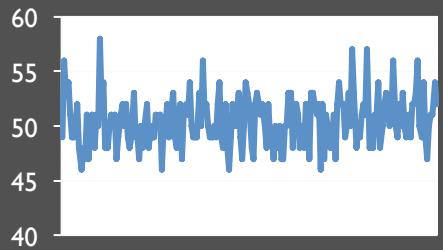
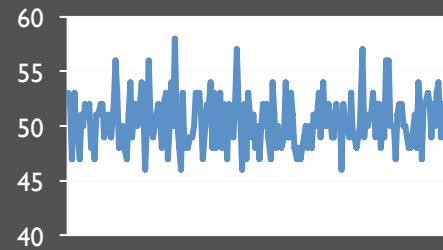
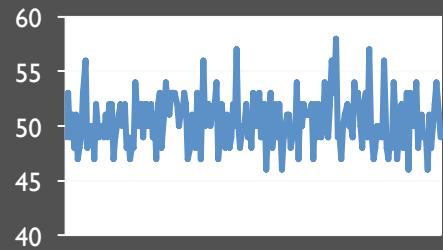
19% chance

245,000+

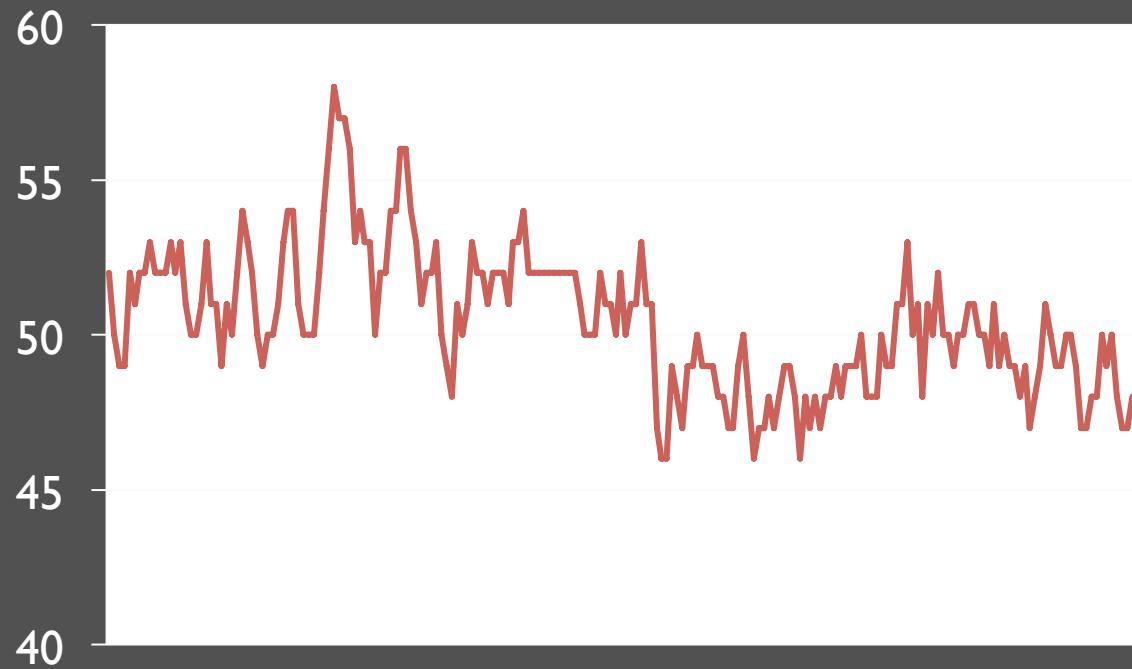
4% chance

# Have People Made Up Their Mind About Obama?

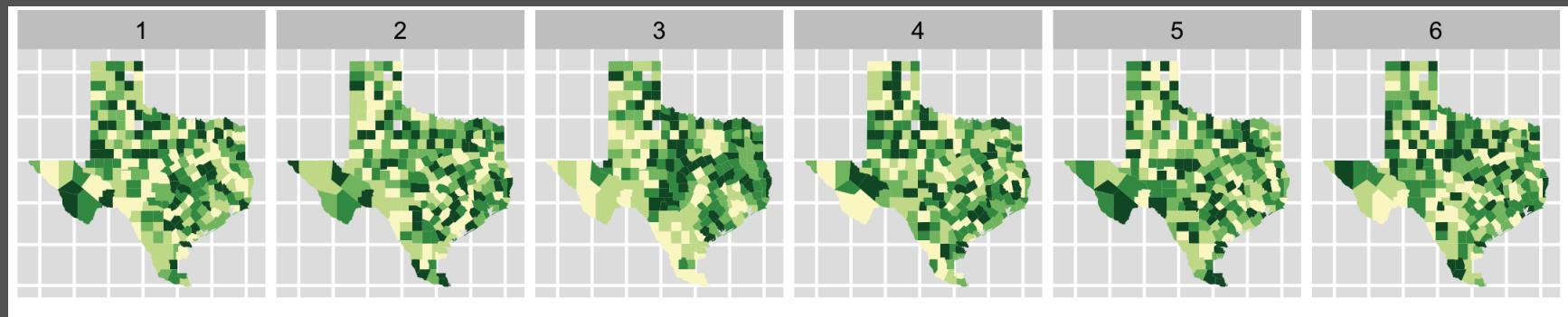




# Visual Lineups

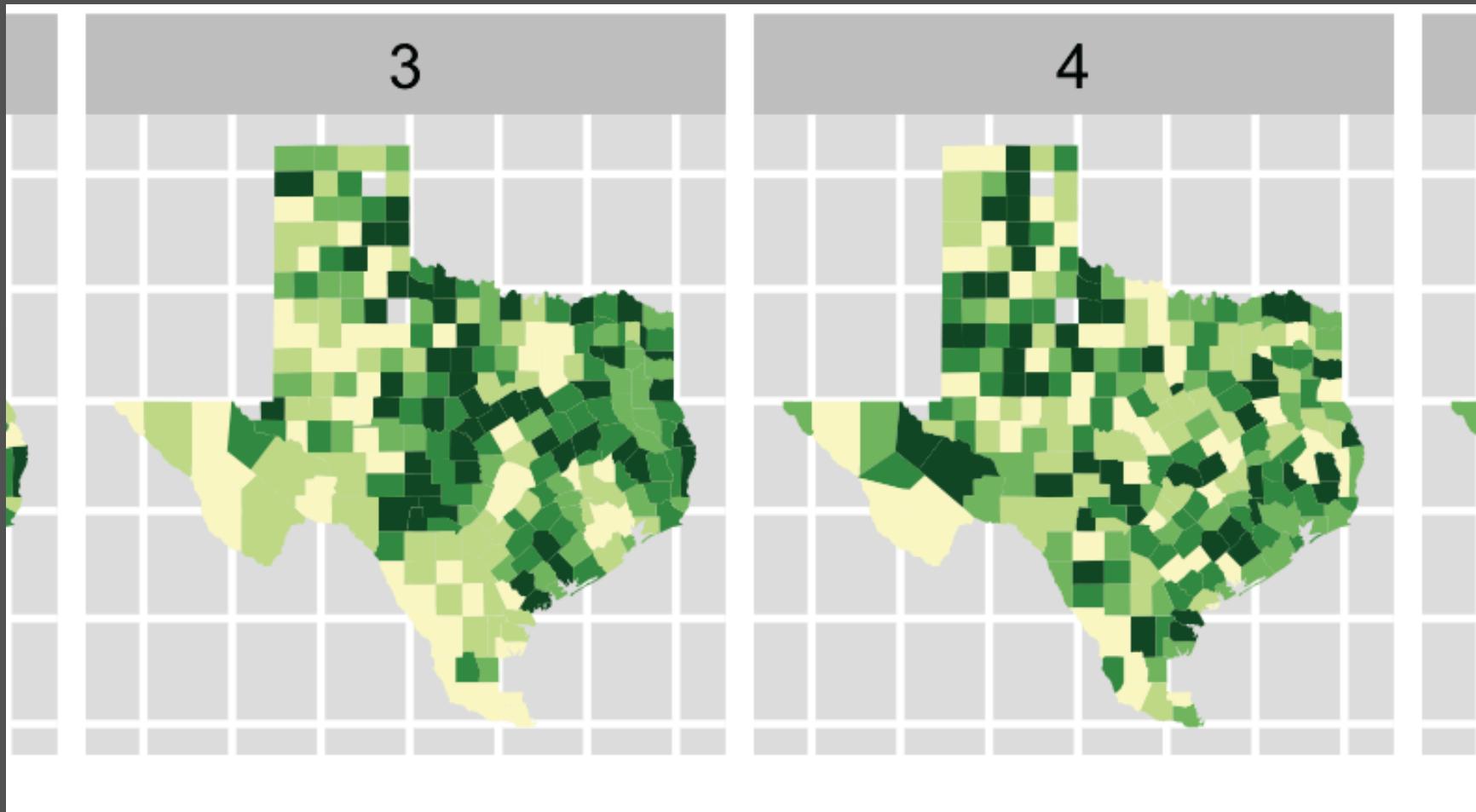


# Visual Lineups



Wickham, Hadley et al. "Graphical inference for Infovis." *IEEE transactions on visualization and computer graphics* 16.6 (2010): 973–9.

# Visual Lineups



# Negative Results

People tend to analyze patterns and make decisions, even if there is “nothing to see.”

Negative or null results can correspond to weak and non-robust visual patterns across a model space.

# Base Rate Fallacy

1% of 40 year old women have breast cancer

The probability a mammogram will detect breast cancer is 80%

The probability of a false positive is 10%.

If a 40 year old woman gets a positive result, what is the probability she has breast cancer?

# Bayes' Law

$$P(A|B) = P(B|A)P(A) / P(B)$$

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$$P(\text{Cancer} | +\text{Test}) = P(+\text{Test}|\text{Cancer})P(\text{Cancer})/P(+\text{Test})$$

# Bayes' Law

$$P(A|B) = P(B|A)P(A) / P(B)$$

$$P(\text{Cancer} | +\text{Test}) = P(+\text{Test}|\text{Cancer})P(\text{Cancer})/P(+\text{Test})$$

$$P(+)=P(+ \wedge C)P(C) + P(+ \wedge \sim C)P(\sim C)$$

# Bayes' Law

$$P(A|B) = P(B|A)P(A) / P(B)$$

$$P(\text{Cancer} | +\text{Test}) = P(+\text{Test}|\text{Cancer})P(\text{Cancer})/P(+\text{Test})$$

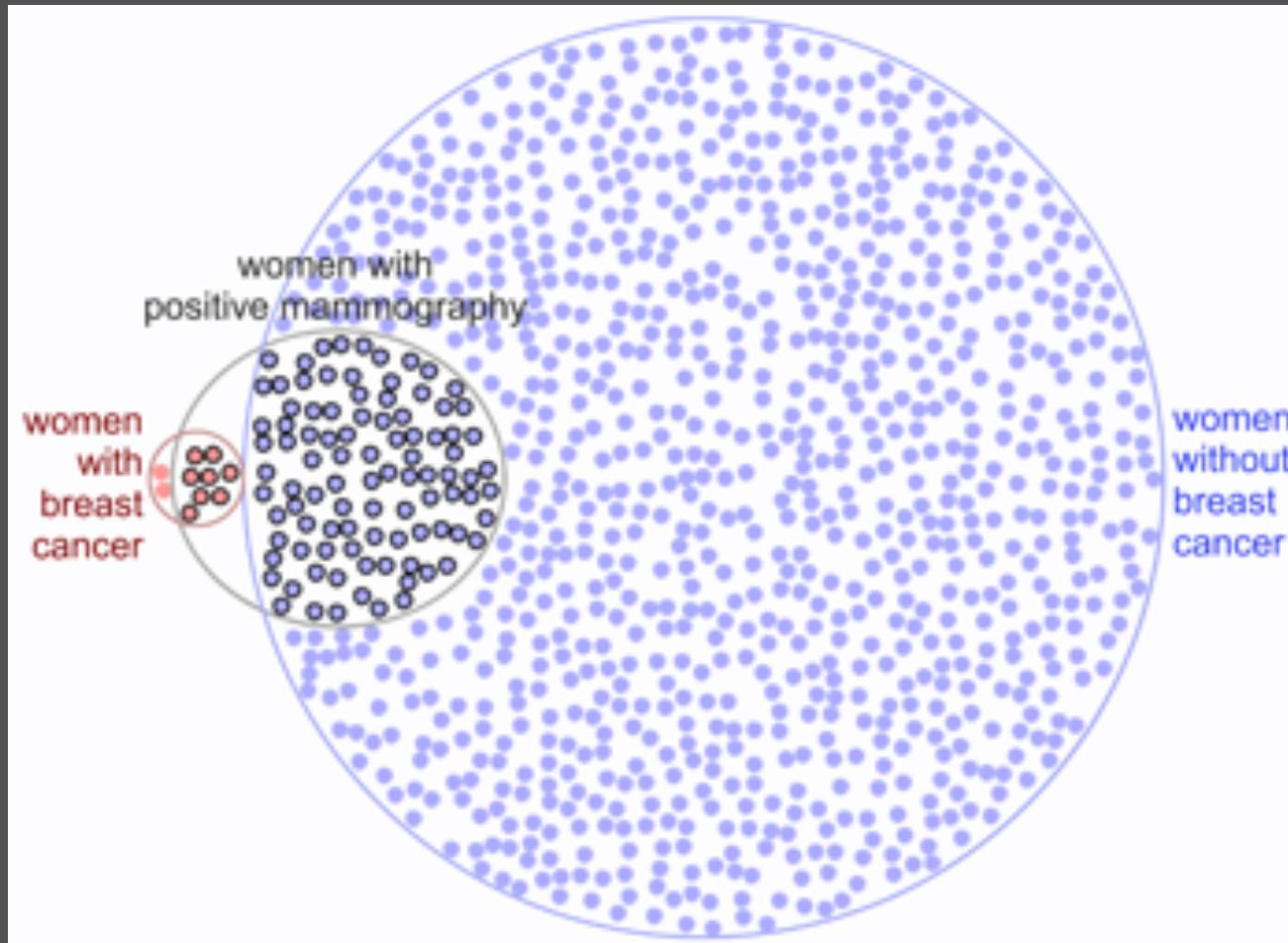
$$P(+)=P(+ \wedge C)P(C) + P(+ \wedge \sim C)P(\sim C)$$

$$P(+)=0.01*0.8 + 0.99*0.1$$

$$P(+)=0.107$$

$$P(C | +) = 0.8 * 0.01 / 0.107 \approx \mathbf{0.075}$$

# Base Rate Fallacy



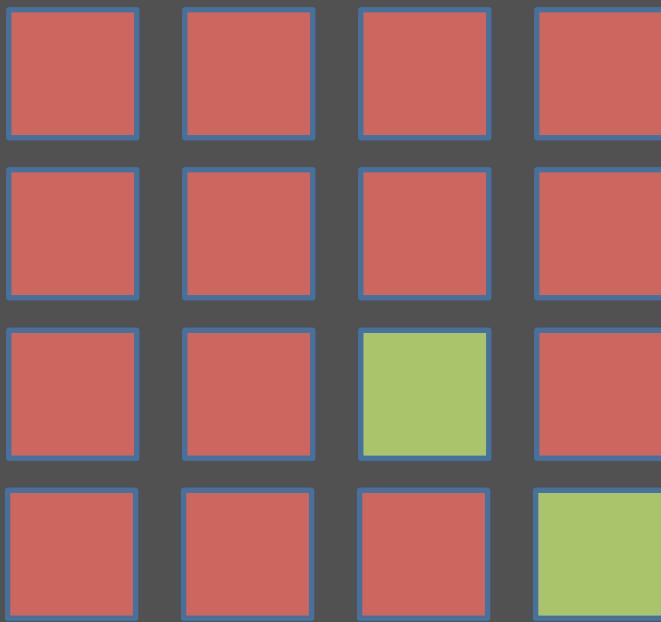
Micallef, Luana, Pierre Dragicevic, and Jean-Daniel Fekete. "Assessing the Effect of Visualizations on Bayesian Reasoning Through Crowdsourcing." *Visualization and ... October* (2012).

# Risk

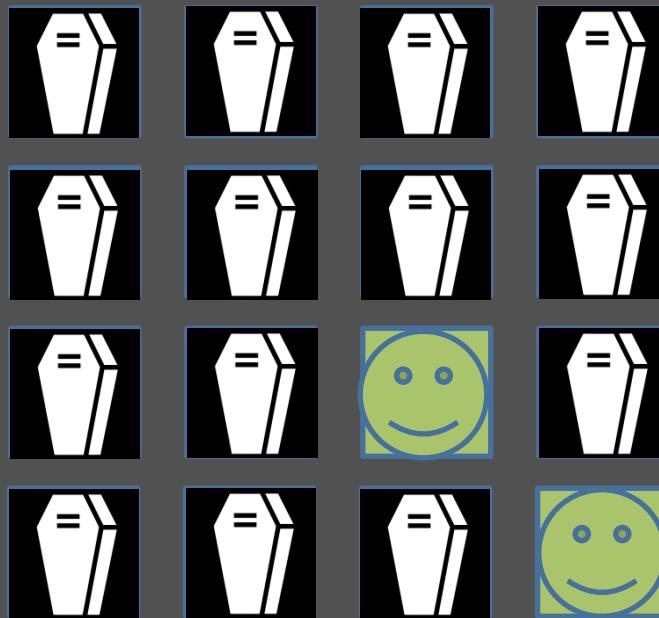
"1 out of every 8 people with small cell lung cancer survive for at least 5 years"

I. Lipkus and J. Hollands. The Visual Communication of Risk. Journal of the National Cancer Institute, 1999.

# Risk



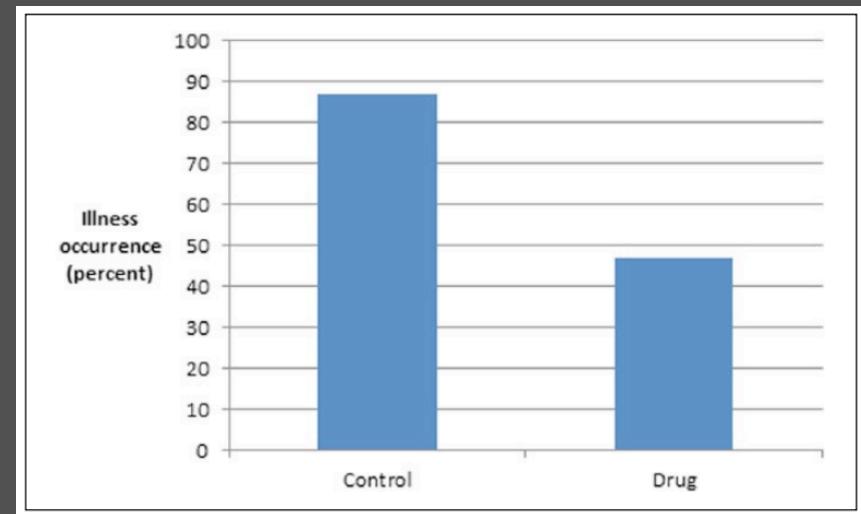
# Risk



"A large pharmaceutical company has recently developed a new drug to boost peoples' immune function. It reports that trials it conducted demonstrated a drop of forty percent (from eighty seven to forty seven percent) in occurrence of the common cold. It intends to market the new drug as soon as next winter, following FDA approval."

# Persuaded by Nothing

"A large pharmaceutical company has recently developed a new drug to boost peoples' immune function. It reports that trials it conducted demonstrated a drop of forty percent (from eighty seven to forty seven percent) in occurrence of the common cold. It intends to market the new drug as soon as next winter, following FDA approval."



Tal, Aner and Wansink, Brian. Blinded with science: Trivial graphs and formulas increase ad persuasiveness and belief in product efficacy. *Public Understanding of Science*, 2016.

# Cognitive Biases

Humans can be quite poor at reasoning about uncertain values.

Minor changes in visual design can influence decision-making for better or worse.

# Conclusion

There are different **types** and **sources** of uncertainty.

We can **quantify** or **model** our uncertainty.

The visual presentation of uncertainty can **clash** with cognitive and perceptual biases.