### Scenarios of Visual Inference - quantifying visual findings -Heike Hofmann

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joint work with Susan VanderPlas and Dianne Cook

### Outline

- Some examples
- A bit about the Lineup Protocol
- Inference in the lineup protocol

# Why Visual Inference?

• Graphics are essential tools for data exploration, but ...

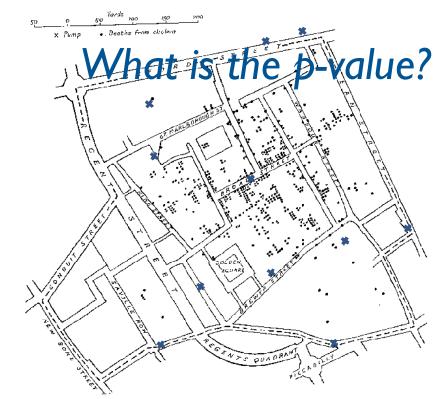


John Snow 1854

- ... post-hoc inferential results are invalid (data fishing, trawling, snooping ...)
- Need: quantitative assessment of significance of graphical finding based directly on graphic

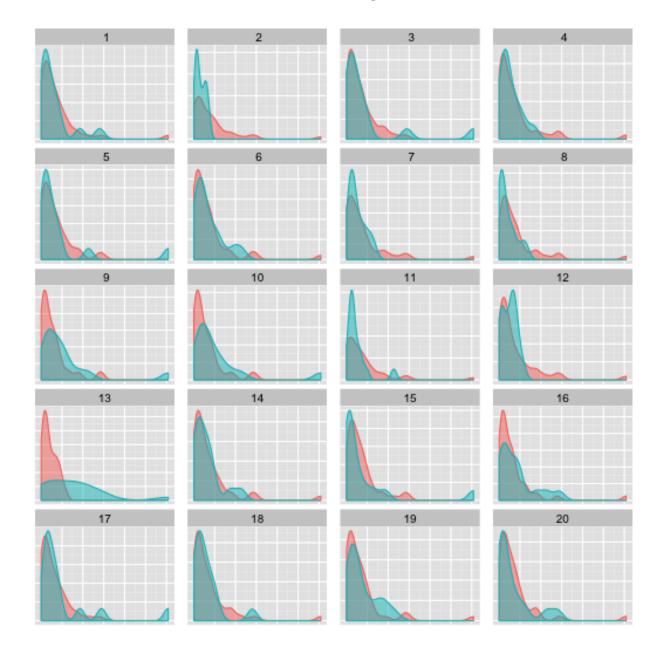
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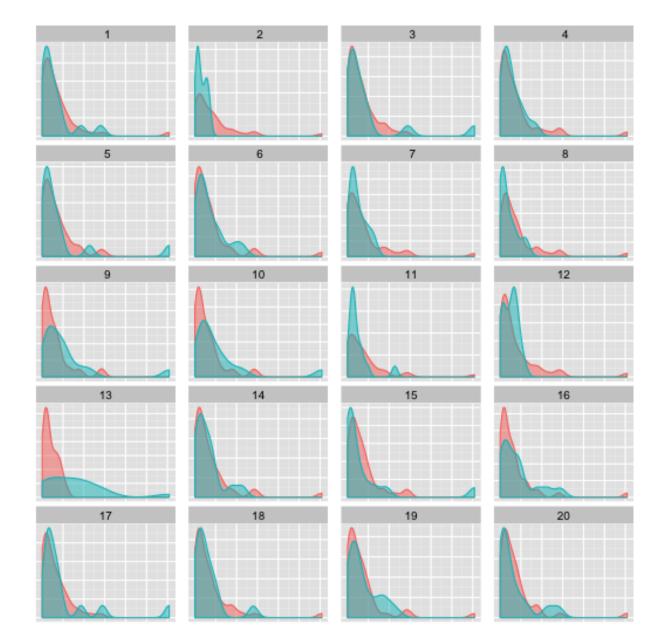
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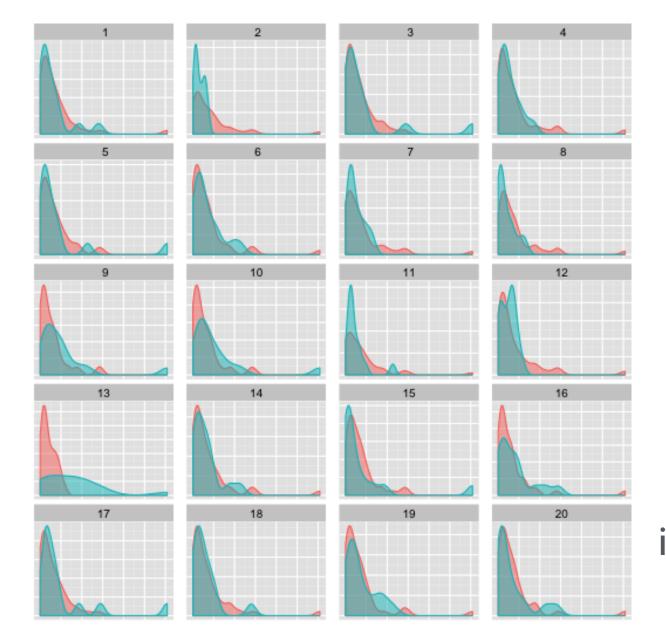
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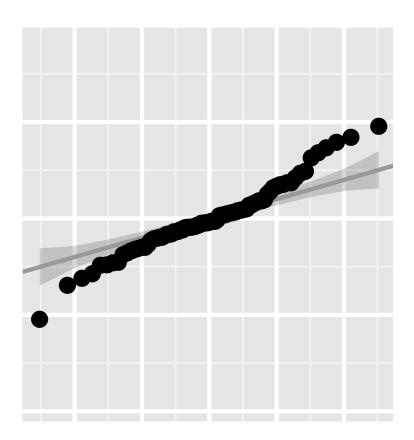


#### data is in panel #13

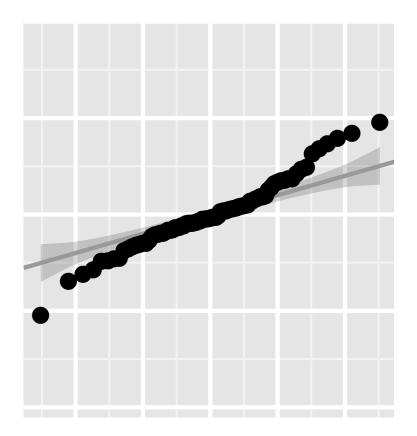


data is in panel #13

20/23 participants identified #13 as the most different

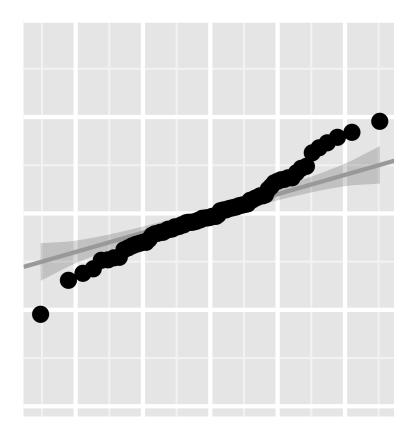


### Normal Q-Q plot



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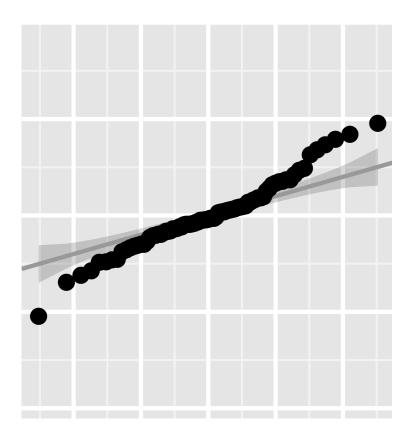
### Obvious deviations from normality assumption

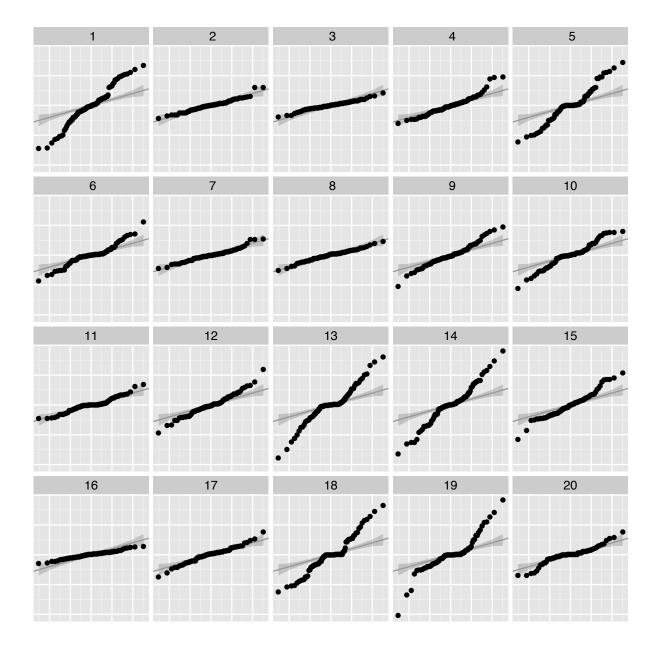


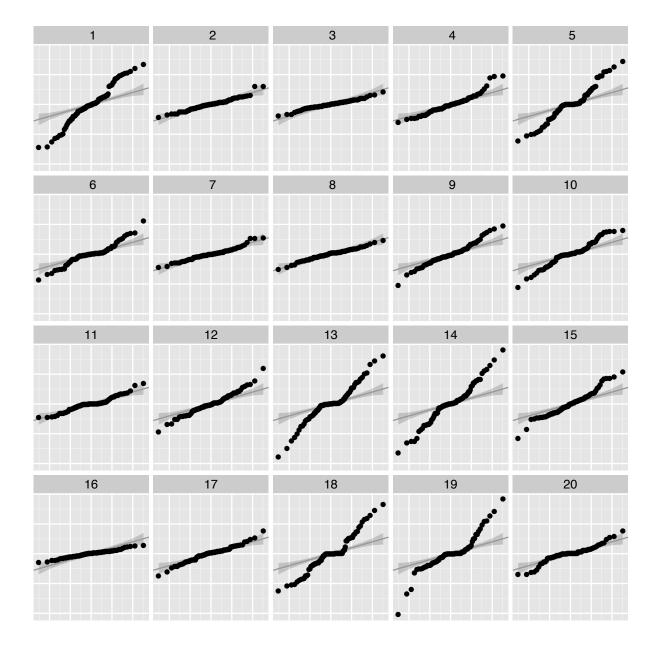
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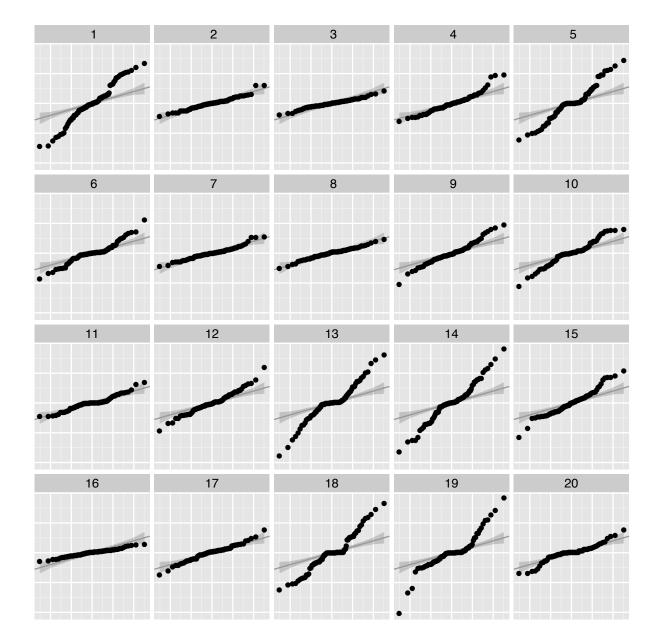
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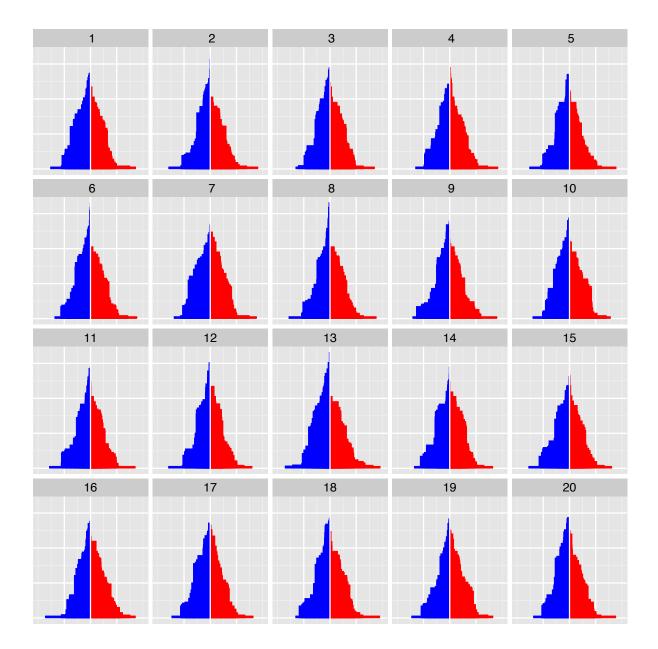


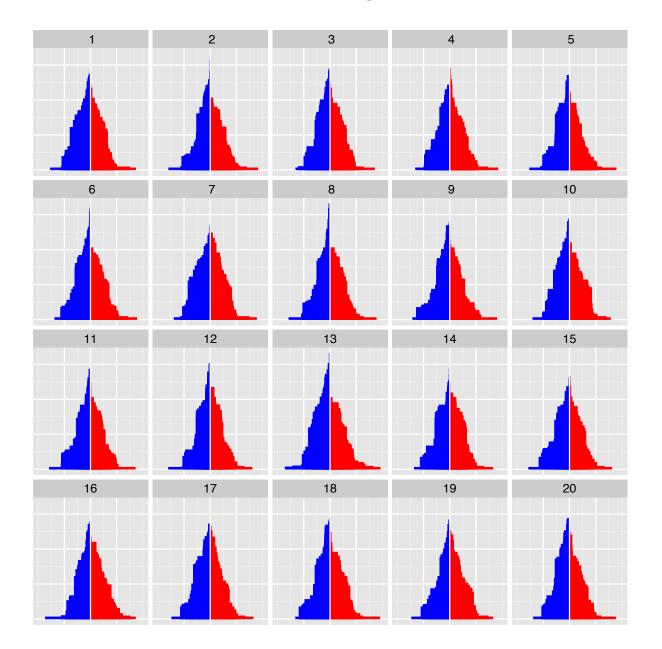
#### data is in panel #10



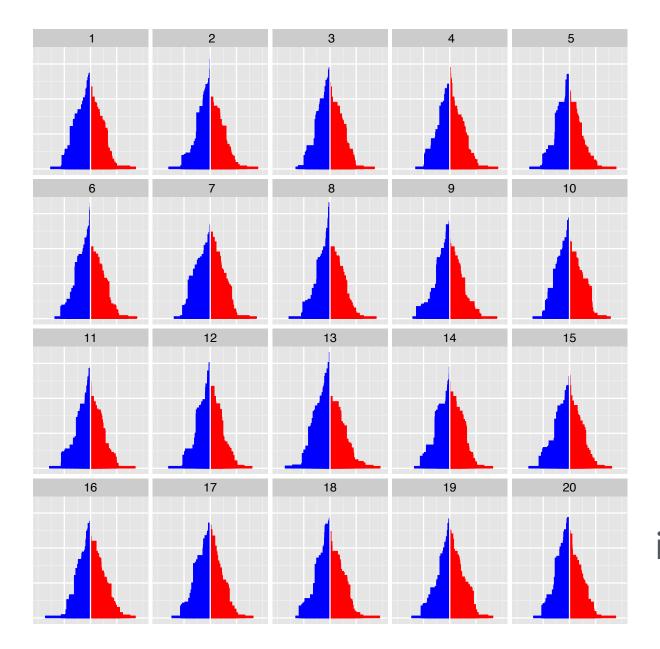
data is in panel #10

0/68 participants identified #10 as the most different



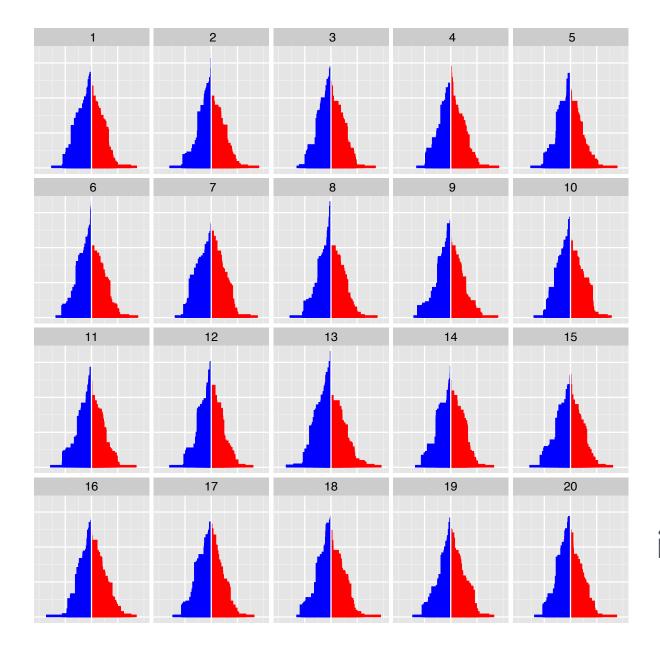


#### data is in panel #13



data is in panel #13

12/72 participants
identified #13 as the
most different



What is the p-value of this finding?

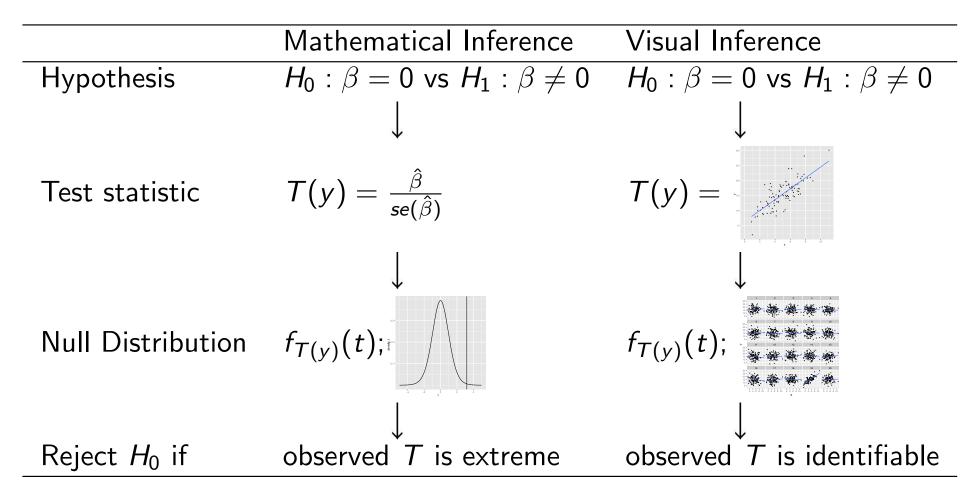
data is in panel #13

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- Lineup protocol in general
- Construction of Lineup in this example





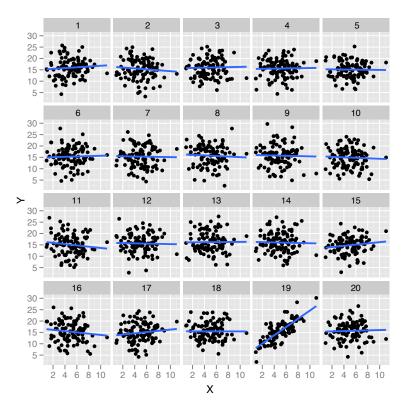
### Test

#### Compare test statistic to values generated consistently with the null distribution Visual

reject null, if test

Classical

statistic is here



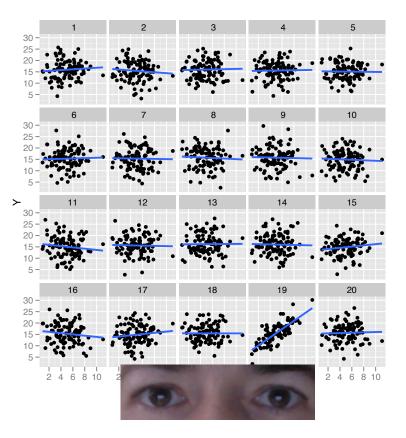
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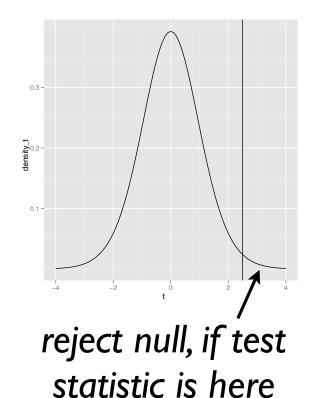
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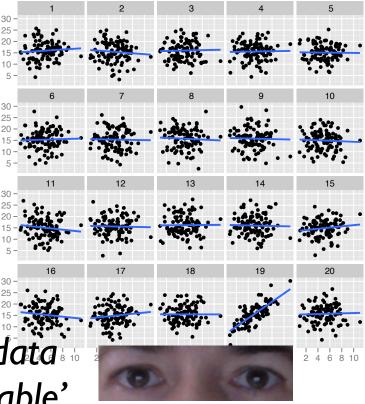
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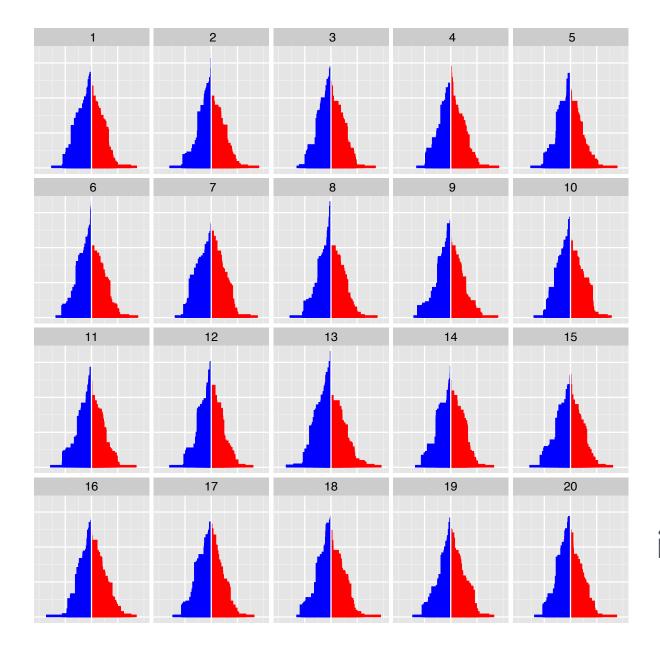


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# Visual p-values

- Assume K independent observers evaluate a lineup
- Let X denote the number of data identifications
- quantify visual p-value:  $Pr(X \ge x | H_0 \text{ true})$



What is the p-value of this finding?

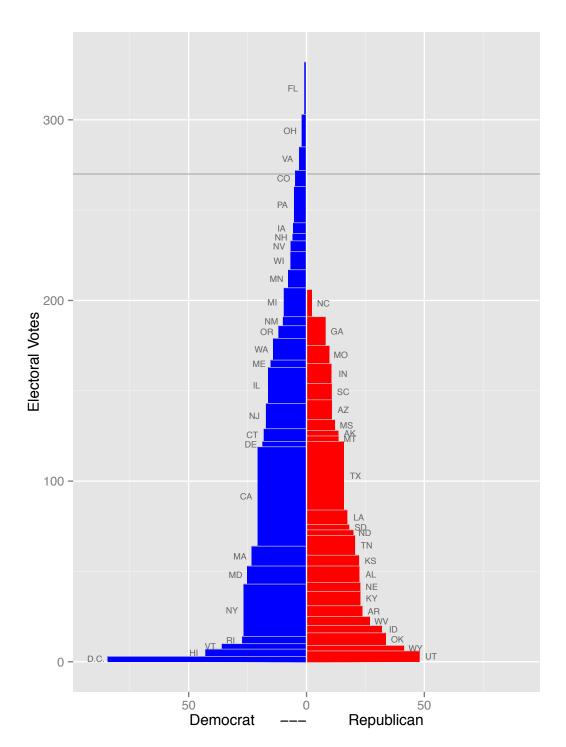
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# The Electoral Building

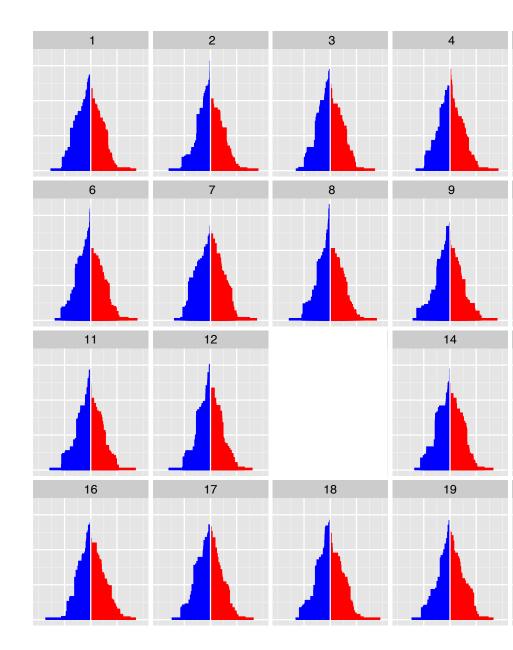
- result from the 2012
   US election
- each state a rectangle: width: margin of majority party over minority height: #electoral votes

the test statistic



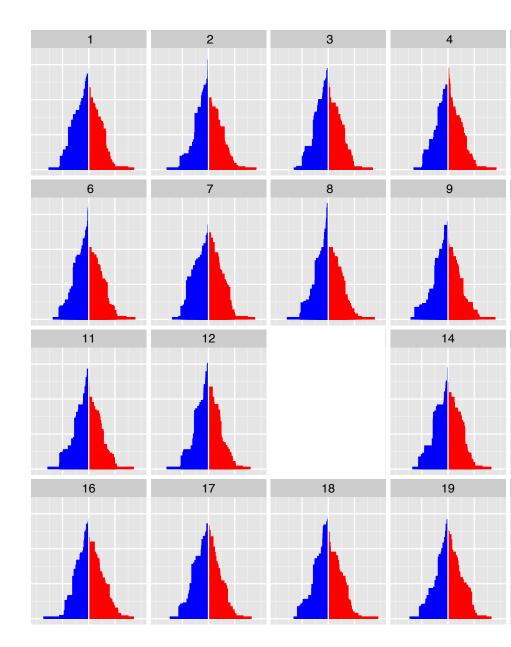
### Null plots

- Null hypothesis: election outcome is consistent with polling results
- Each null plot consists of sample from a pollster's predictions



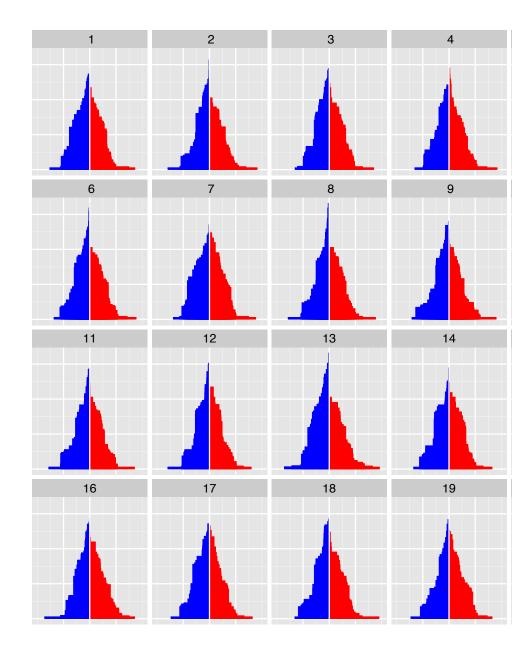
### Lineup

- Data is randomly placed among the null plots
- If the data is indistinguishable from the null, the election results are consistent with the poll



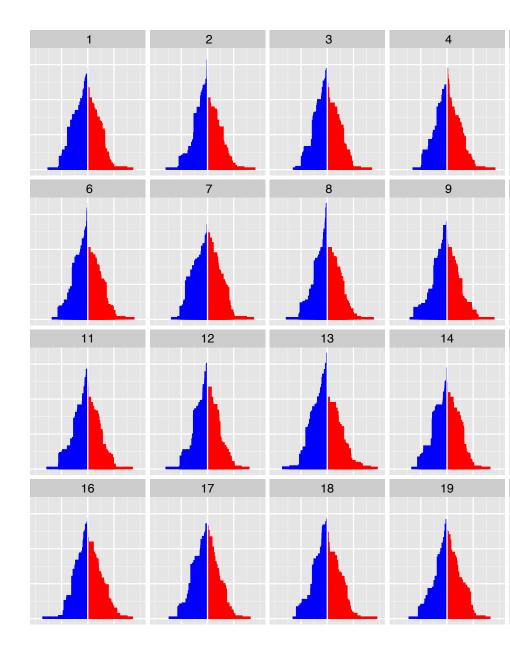
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visual p-value:  $P(\# data \ plot \ picks \ge 12)$ 

# Data from lineup evaluation

- For lineup of size m we observe
   X = (X<sub>1</sub>, ..., X<sub>m</sub>) ~ Mult<sub>p1, p2, ..., pm</sub>
- with  $0 \le p_i \le I$  and  $\sum_i p_i = I$
- w.lo.g. data plot in panel m, ie X<sub>m</sub> ~ Binom(K, p<sub>m</sub>) K independent evaluations
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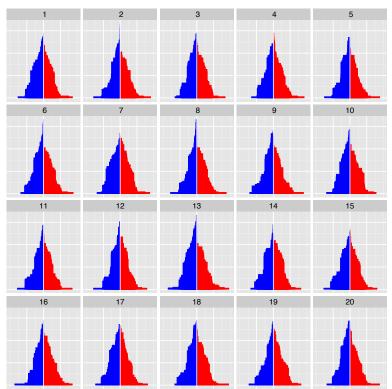
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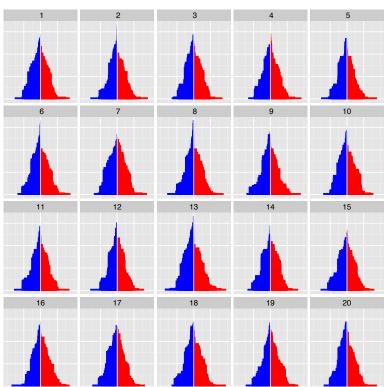
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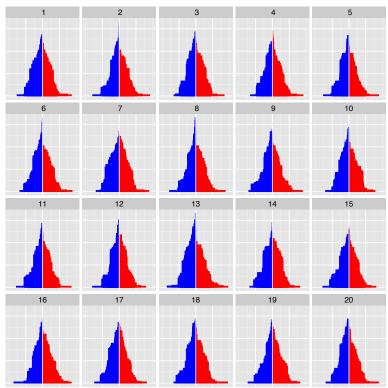
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### fails the sniff test!

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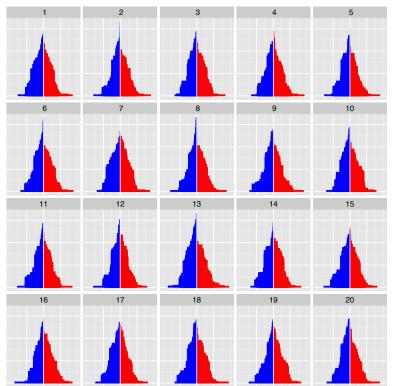


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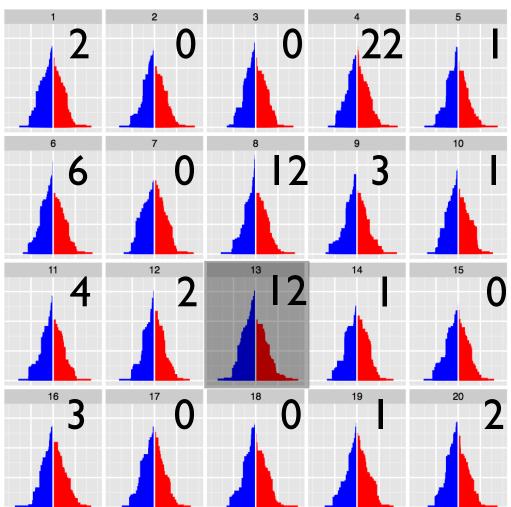
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Generally:  $p_m$  depends on  $p_1, ..., p_{m-1}$ , varies with lineup



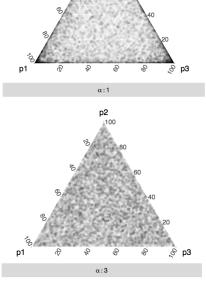
# Null Distribution of p

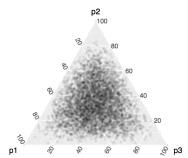
- Two other plots were selected at least as often as the data plot
- Distribution of null plot picks far from uniform



# Null Distribution of p

- p<sub>i</sub> is probability to pick panel i
- Assume that under the null, all panels have the same distribution:
   p = (p<sub>1</sub>, ..., p<sub>m</sub>) ~ Dirichlet(α), α > 0 a flat Dirichlet distribution





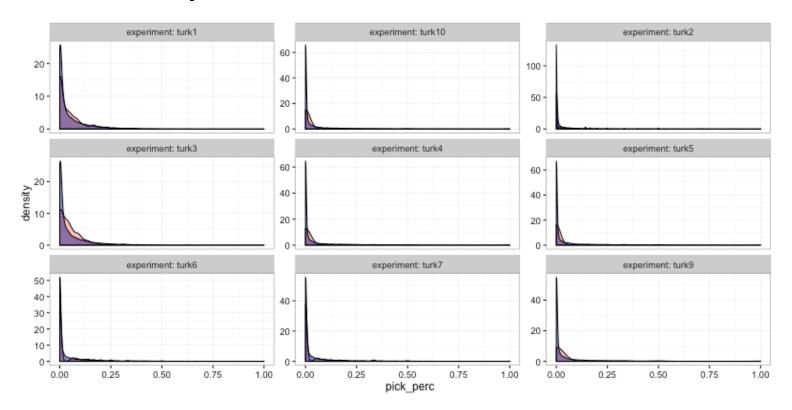
 Estimate rate α from observed (p<sub>1</sub>, ..., p<sub>m-1</sub>)' where (p<sub>1</sub>, ..., p<sub>m-1</sub>)' is rescaled without data plot

- flat Dirichlet( $\alpha$ ) for ( $p_1, ..., p_{m-1}$ )' seems reasonable
- no obvious preference for location

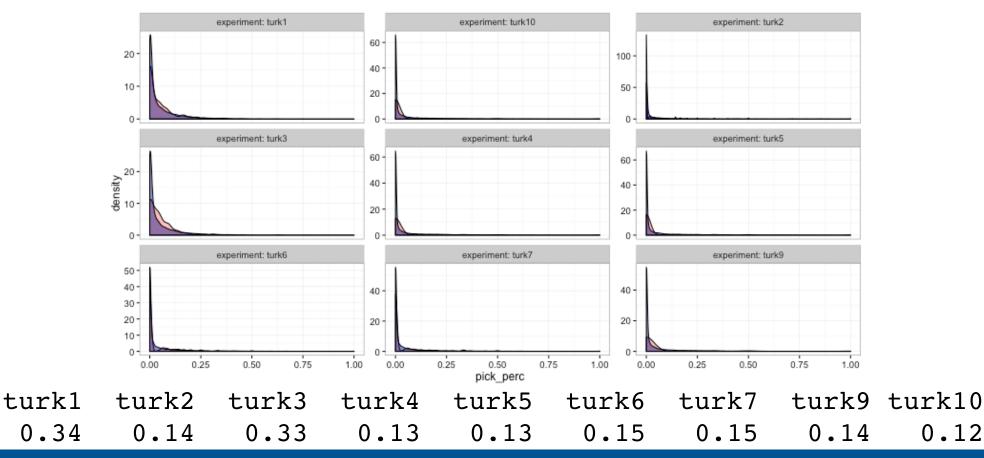
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Dirichlet distributions estimated for each of nine different experiments

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### visual p-value

p-value based on Binom(72, 1/20)
 P(X ≥ 12) = 0.00023

 1
 2
 3
 4
 5

 6
 7
 8
 9
 10

 6
 7
 8
 9
 10

 11
 12
 13
 14
 15

 11
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 16
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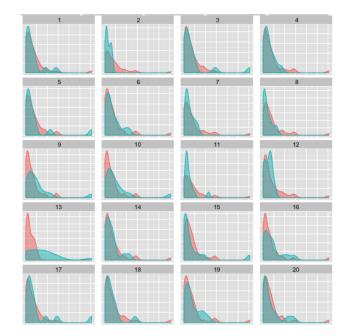
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• p-value based on Dirichlet approach:  $P(X \ge 12) = 0.11396$ 

### visual p-value

p-value based on Binom(23, 1/20)
 P(X ≥ 20) ≤ 0.00001

• p-value based on Dirichlet approach:  $P(X \ge 20) = 0.001842$ 



20/23 participants identified #13 as the most different

# Dirichlet distributions for null

- seems to work in practice theoretical densities and observed frequencies of picking null plots match
- α gives a rough estimate of the spread of null distribution/difficulty of a lineup (without regarding : small α = small number of null plots attract picks)
- Weirdly, strong signal in data plot makes estimating α harder: Rorschach for α

### Conclusions

- Use lineup scenario to get valid p-values for visual findings
- useful in situations where conventional methods break down
- lineups allow us to ask for 'why' ... insight to visual reasoning of participants