



MIAMI UNIVERSITY

Lady Tasting Tea Lineups for Visual Inference

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Lady Tasting Tea ¹



- Ronald Fisher and Muriel Bristol working at Rothamsted
- Claimed she could tell if tea or milk added first
- Blind taste test: four milk first, four tea first
- Fisher's Exact Test → follows hypergeometric if guessing

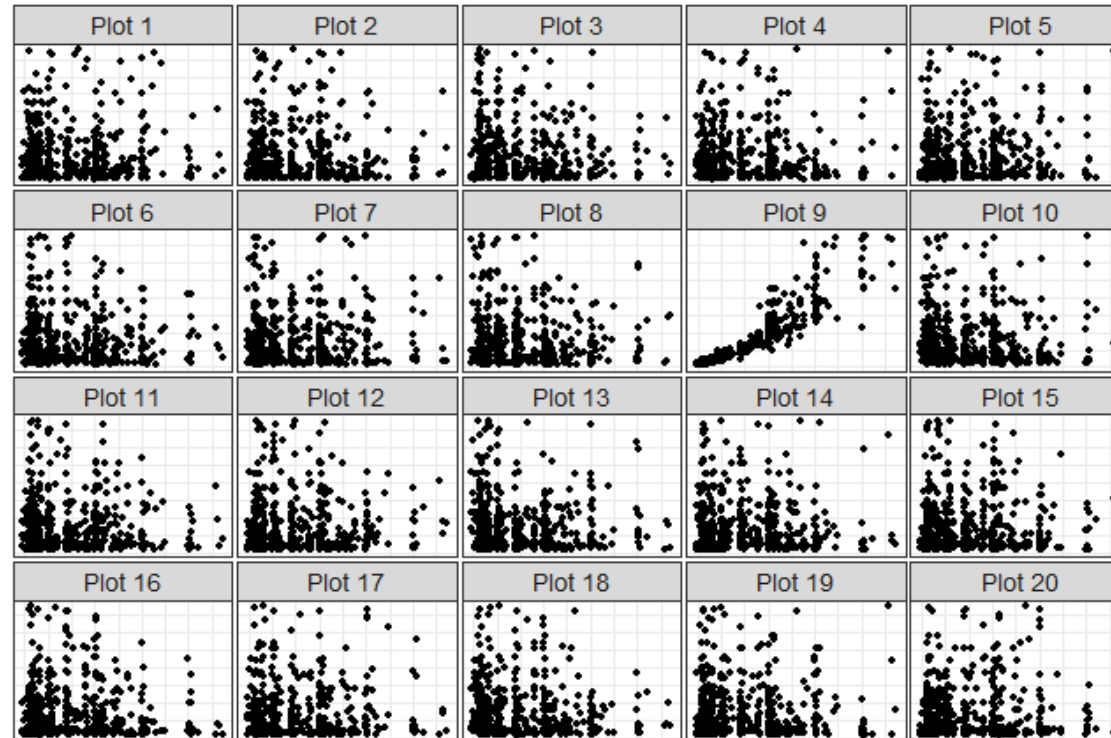
[1] Fisher, R. A. (1960)

Lineups



Can the witness pick the criminal out of a randomized lineup of people?

Lineups (for Visual Inference) ²



Can the statistician pick the real data out of a randomized lineup of data simulated under the null?

[2] Buja, A., Cook, D., Hofmann, H., Lawrence, M., Lee, E. K., Swayne, D. F., & Wickham, H. (2009)

Lineups (for Visual Inference)

- Plot of real data hidden in set of $K-1$ plots of data generated under null model

Lineup Interpretations - One Viewer

- If a viewer can pick out the real data ($p\text{-value}=1/K$) \rightarrow reject the null
- If a viewer can't pick out the real data ($p\text{-value}=1$) \rightarrow fail to reject the null

Lineup Interpretations - Many Viewers

- Each person attempts to pick out real data
- Sum of correct guesses distributed Binomial($n, 1/K$) if viewers independent



Our Work

- Research Team: George Woodbury, Seonjin Kim and myself
- Work started with George's masters project improving visual inference with one person
- After masters, George came back with a new idea...

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Mashup: Tea Tasting + Lineup Plots

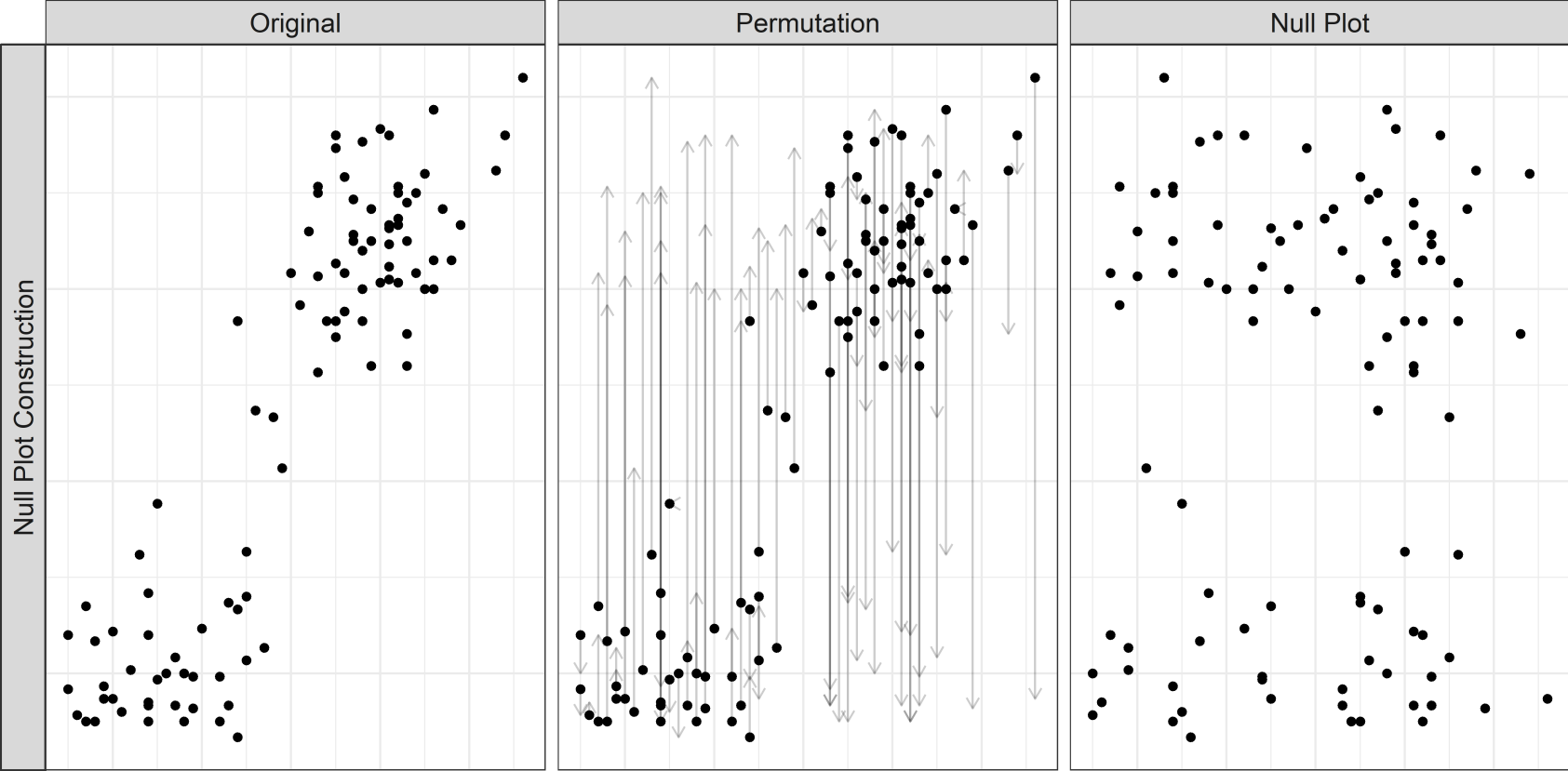
- Applying experimental design from the lady tasting tea
- Randomized lineup of with multiple null and *multiple* target plots
- Viewer (*tea-taster*) tasked with identifying target plots



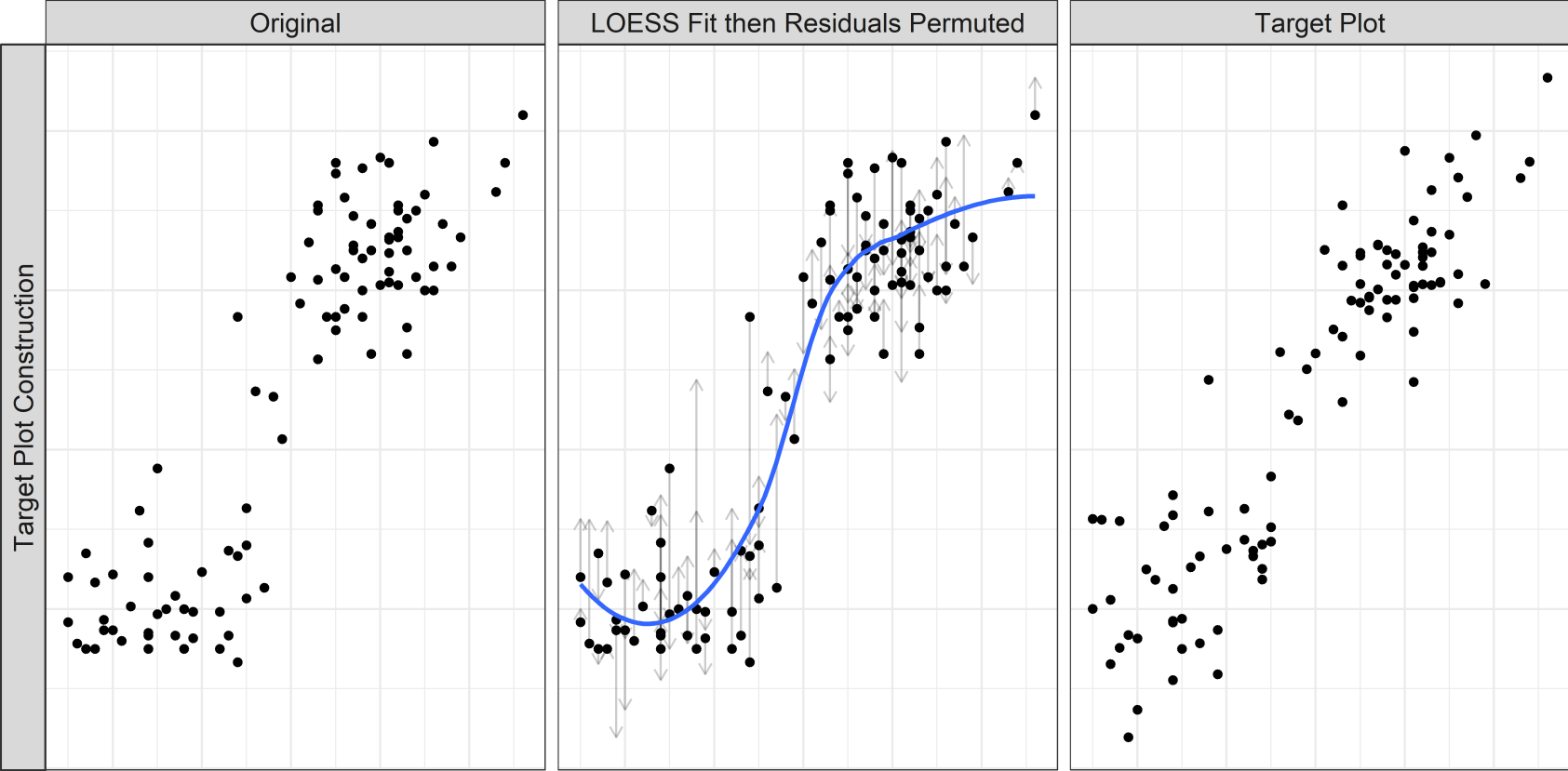
Methods



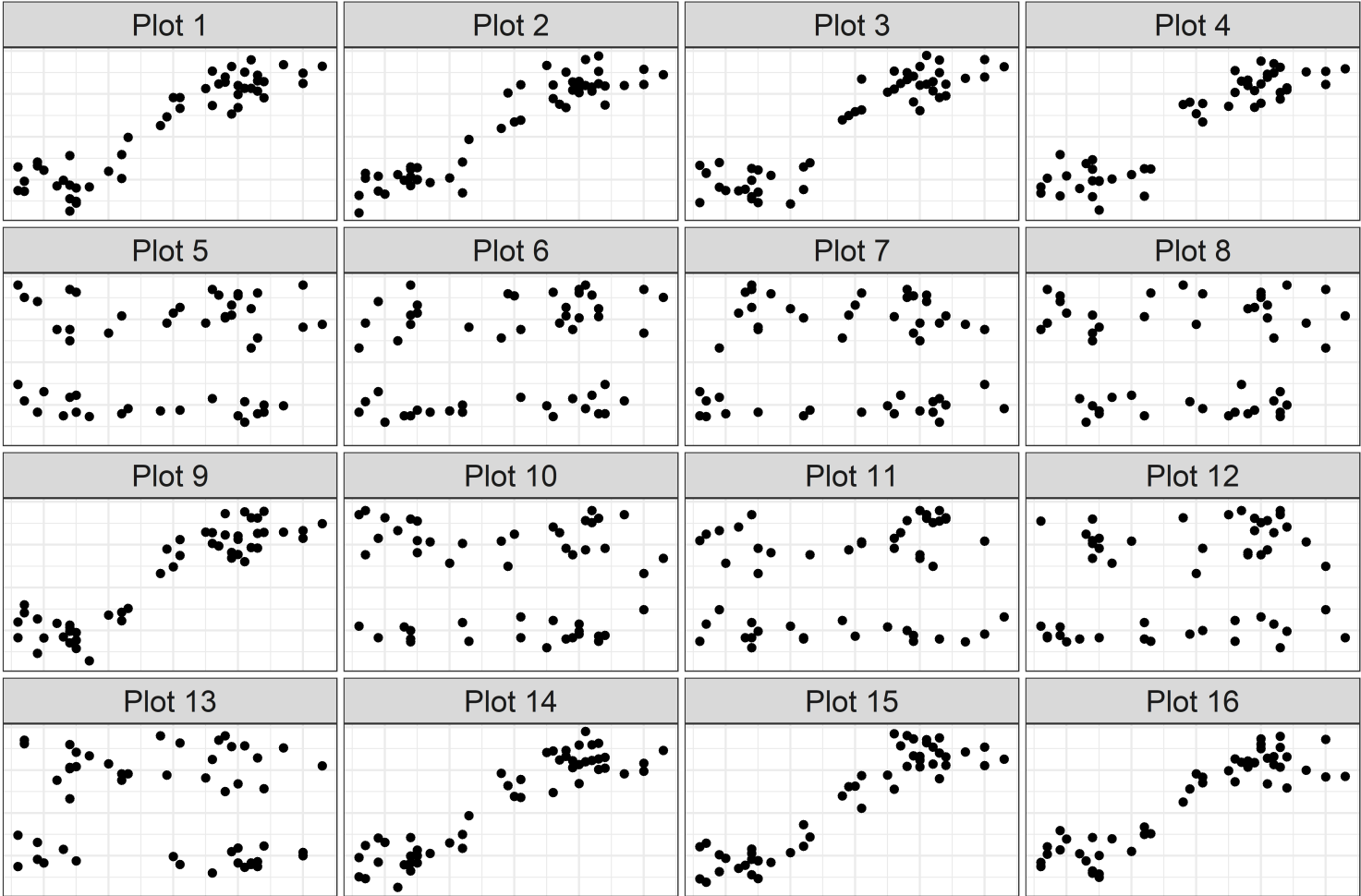
Generating Null Plots for Tea-Tasting Lineups



Generating Target Plots for Tea-Tasting Lineups



Example Tea Tasting Lineup



Properties

- Looks similar to traditional lineup for visual inference but task different
- p-values for single TT lineup evaluation are no longer binary
- p-values follow hypergeometric *if null and target plots indistinguishable for data generated by the null*

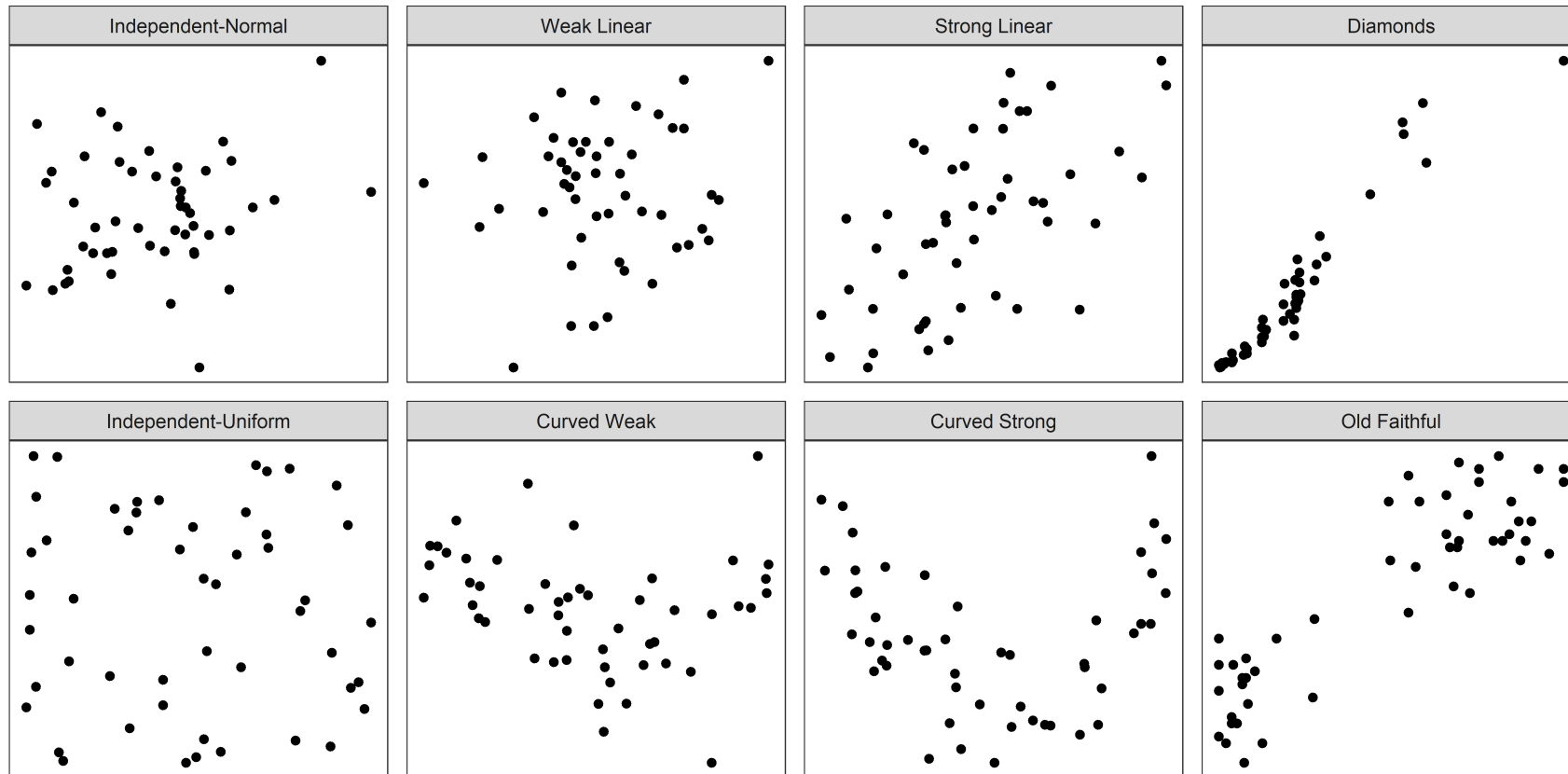
Open Questions

- 1. Does the TT lineup have discriminative power in practice?**
- 2. Are correct guess counts hypergeometrically distributed for a true null?**



Survey

- Participants presented with eight TT lineups based on eight datasets



Survey

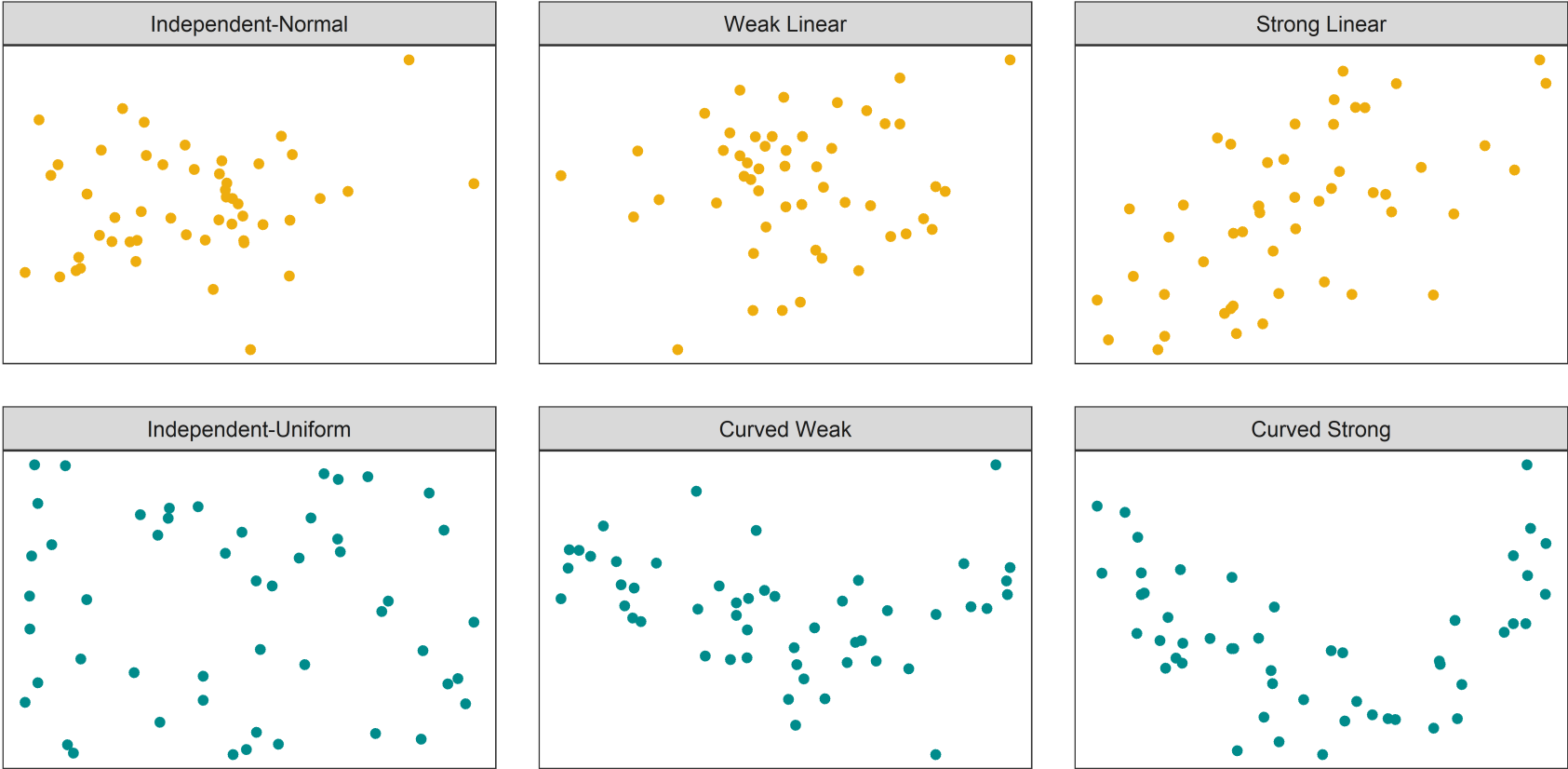
- Administration:
 - distributed to students and faculty of Miami University Stat Department
 - Anonymous drop-box for return
- Content
 - Tea-tasting lineups from 8 different datasets
 - Each lineup had 8 null plots and 8 target plots
- Randomization:
 - Datasets uniquely simulated/sampled for each survey
 - Random order of lineups on survey
 - Random plot ordering within lineups
 - Permutation step for each plot construction
- 45 participants
 - 24 Undergrad, 14 Grad, 6 Faculty, 1 Unknown
 - 41 completed all eight lineups



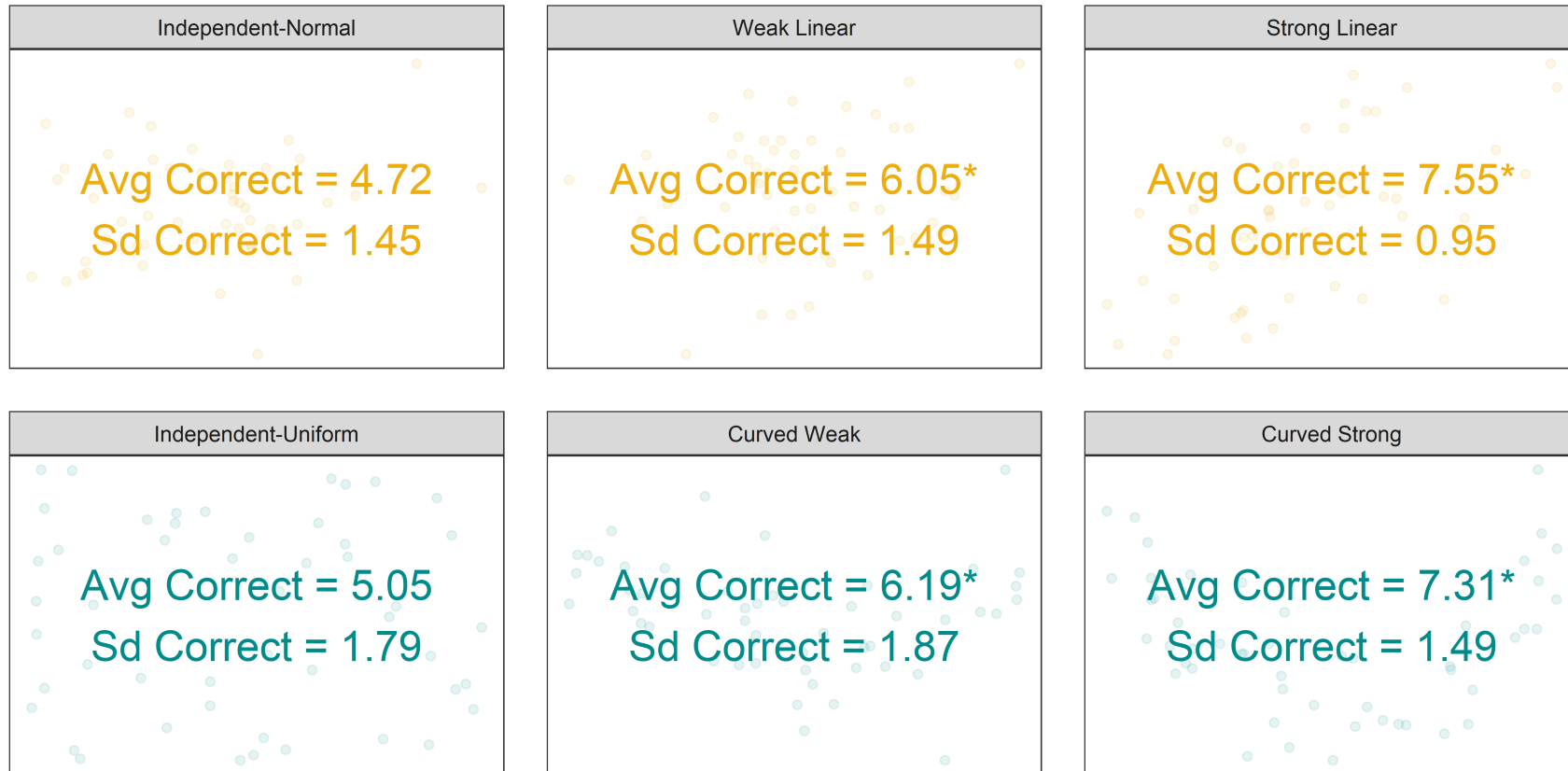
Results



1. Does the TT lineup have discriminative power in practice?

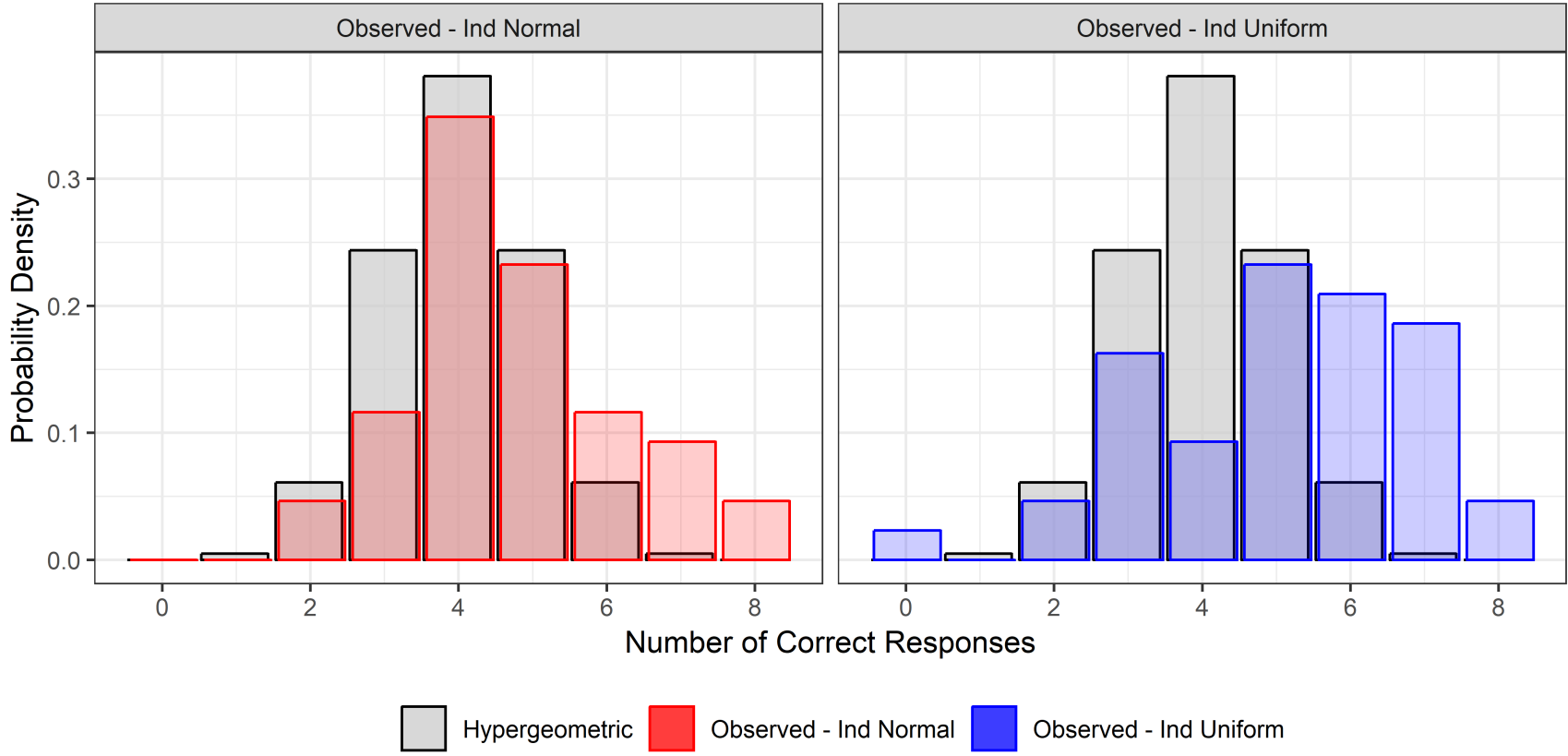


1. Does the TT lineup have discriminative power in practice? Yes!



* t-test strongly suggests more correct answers than lower strength relationship

2. Are the TT lineup p-values hypergeometrically distributed?



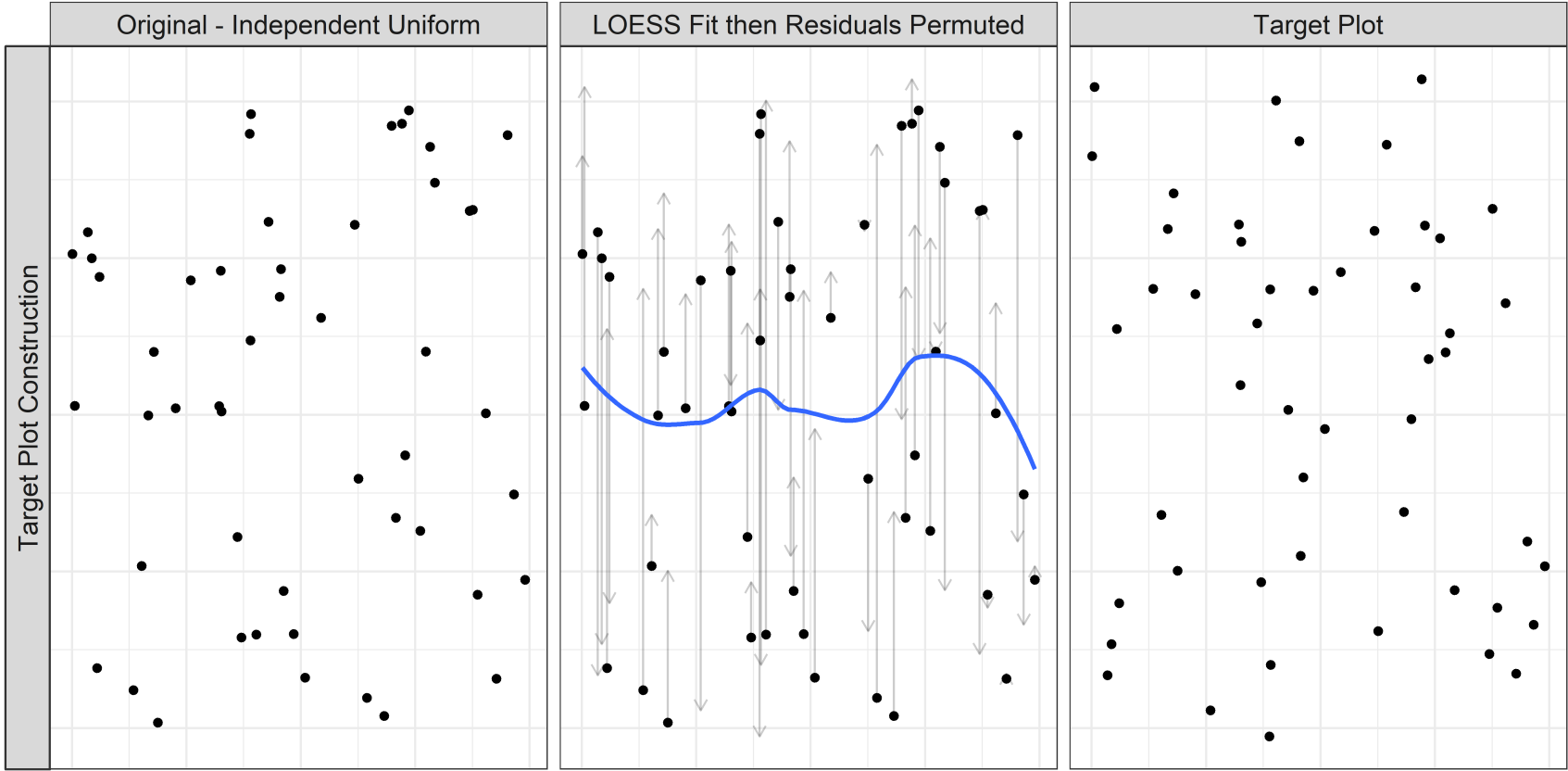
2. Are the TT lineup p-values hypergeometrically distributed? No.

This would be true, **assuming** that null plots and target plots are indistinguishable under the null

So why are target plots noticeably different?

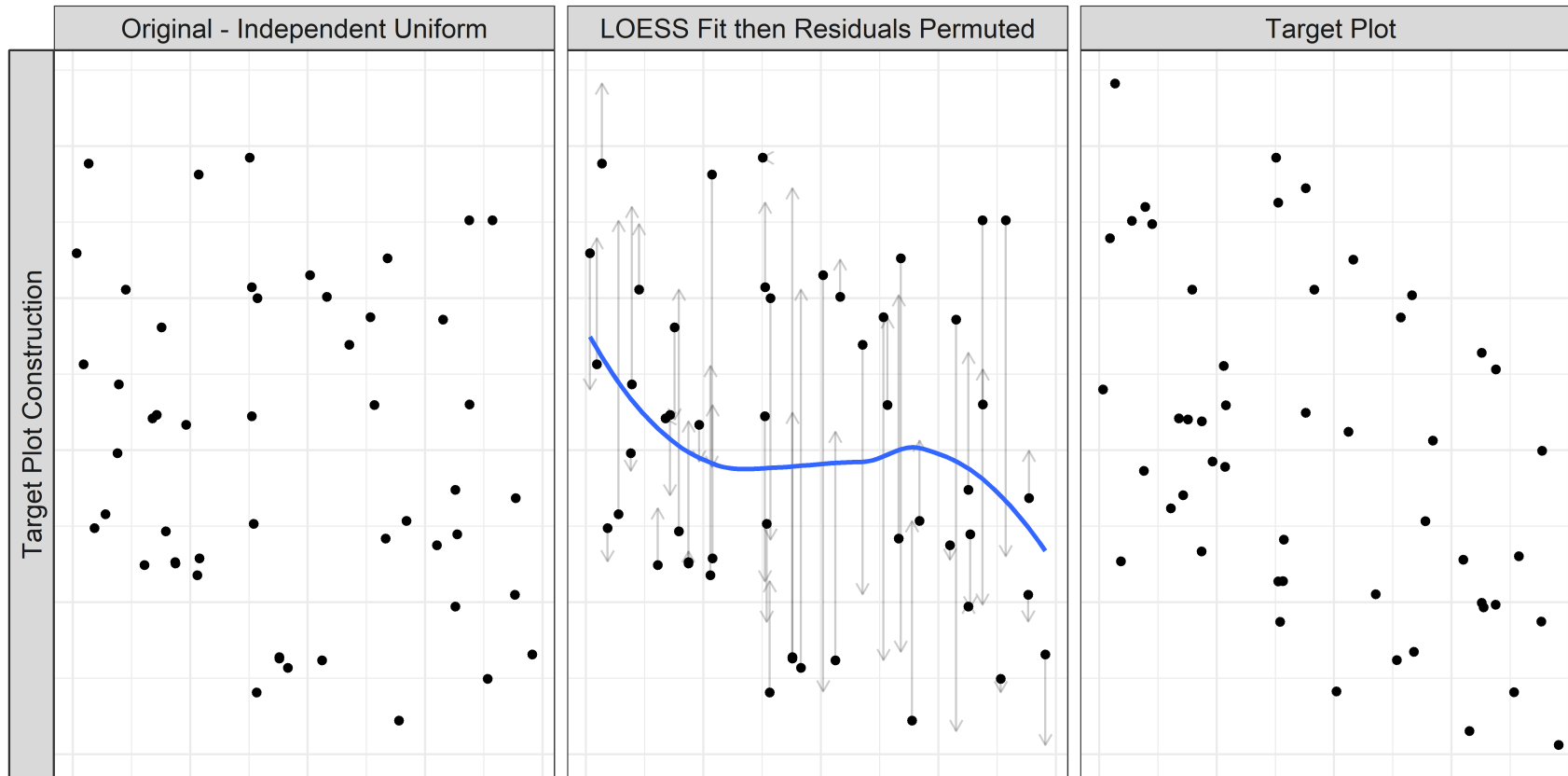


2. Are the TT lineup p-values hypergeometrically distributed? No. Why not?



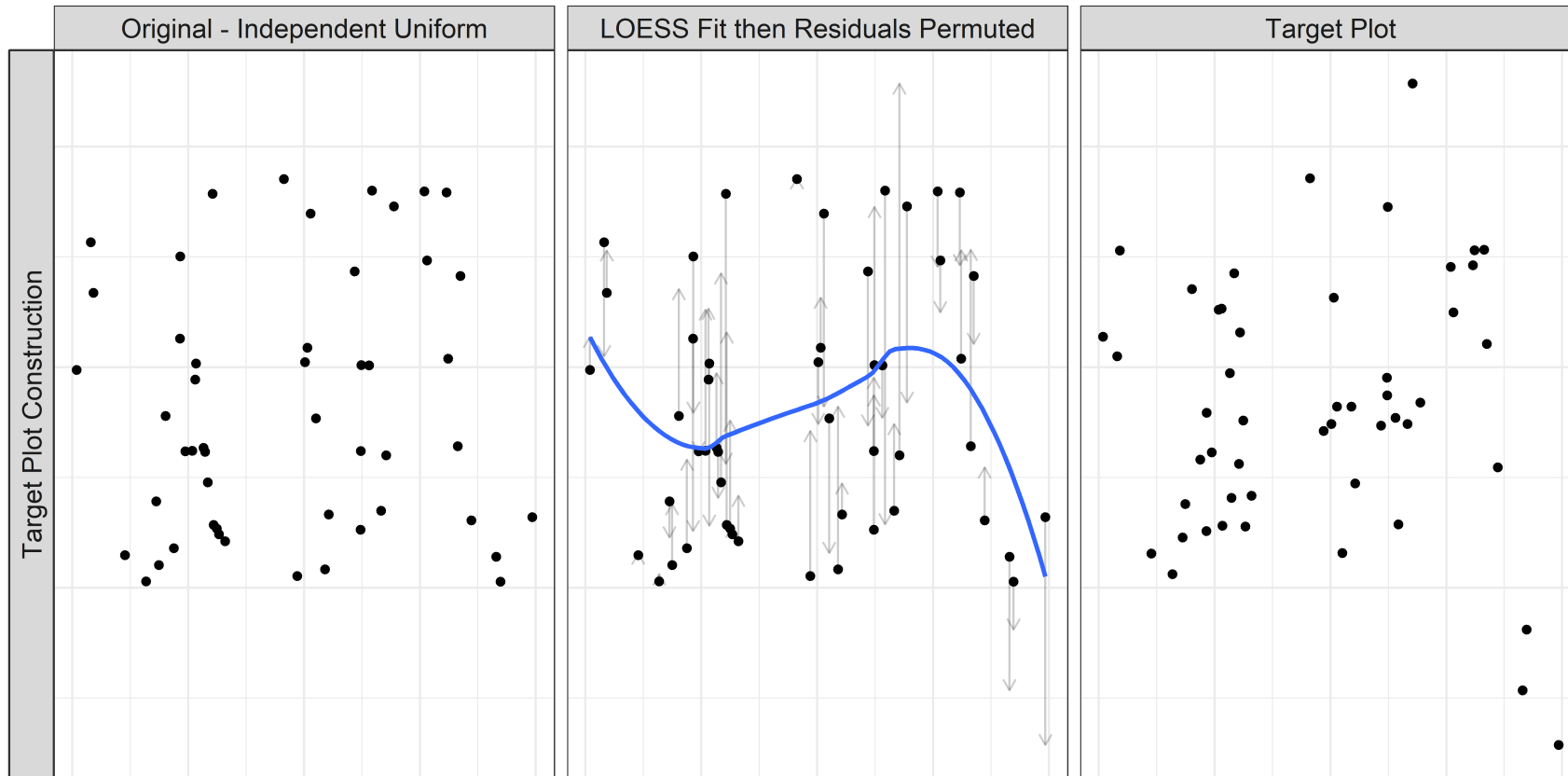
Sometimes data from the null are "stereotypical"

2. Are the TT lineup p-values hypergeometrically distributed? No. Why not?



Sometimes data from the null are "weird" (type I errors)

2. Are the TT lineup p-values hypergeometrically distributed? No. Why not?



Sometimes data from the null are "stereotypical", but our method are unstable

Conclusions



What did we learn?

1. Does the TT lineup have discriminative power in practice?

Yes, more correct guesses for data with stronger relationship

2. Are correct guess counts hypergeometrically distributed for a true null?

No, issues with LOESS tail-instability.

Should consider alternative methods for generating target plots (wider smoothing span or bootstrapping)

Implementation

- R package implementation is available at github.com/kmaurer/teaTasteR

```
devtools::install_github("kmaurer/teaTasteR")
```



References

Literature

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References

Software and Data

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Thanks!

Slides created via the R package **xaringan**.

