

# Clusters beat Trend!?

# Testing Feature Hierarchy in Statistical Graphics

Susan VanderPlas & Heike Hofmann,

Iowa State University

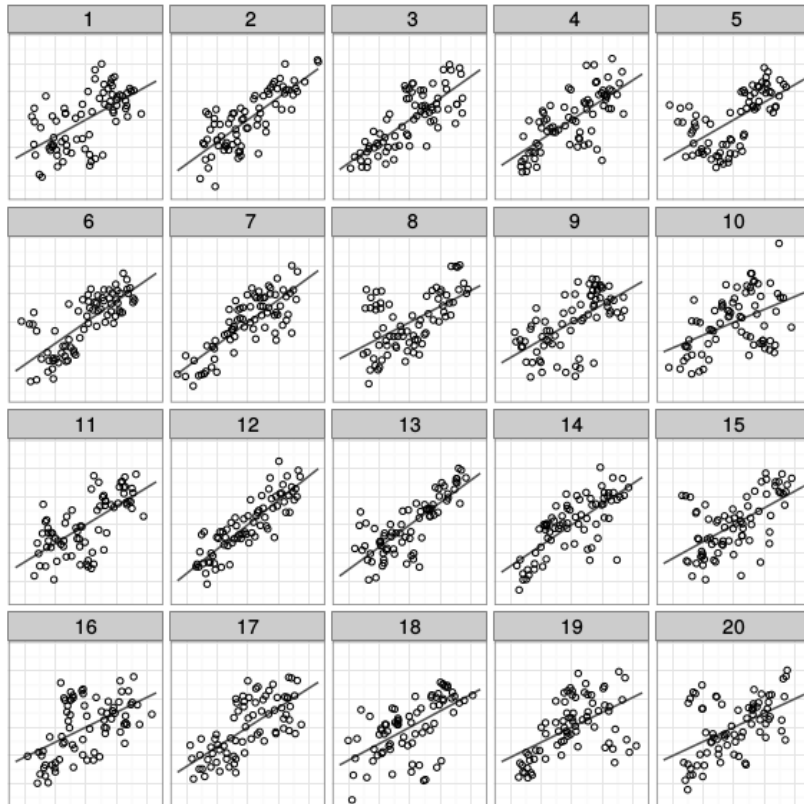
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# Outline

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  - Target Identification
  - Clusters vs. Trend
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# Introduction

# Which plot is the most different?



## Participant Responses

Plot 12: 52.2% (Trend target)

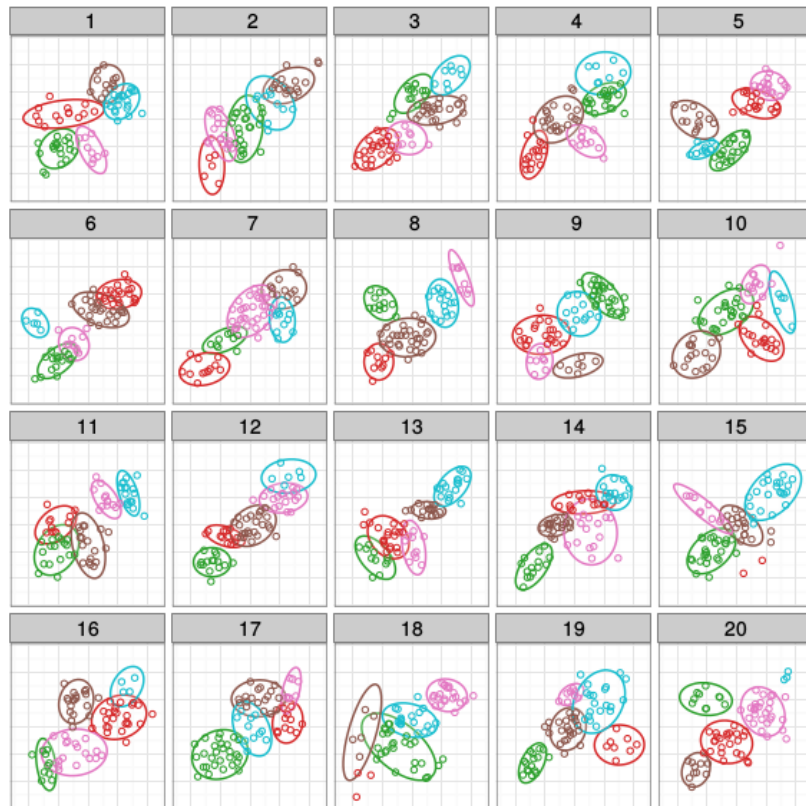
Plot 5: 17.4% (Cluster target)

Other: 30.3%

Sample size: 22

Trend target: 12, Cluster target: 5

# Which plot is the most different?



## Participant Responses

Plot 12: 9.4% (Trend target)

Plot 5: 28.1% (Cluster target)

Plot 18: 31.2%

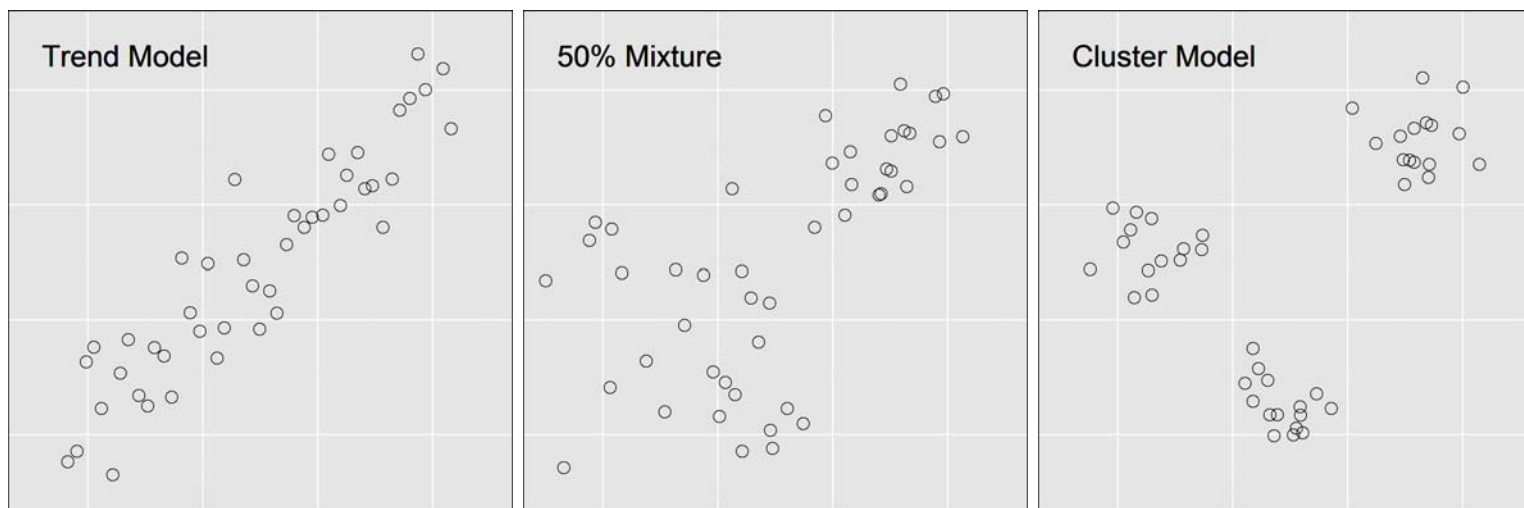
Other: 31.1%

Sample size: 31

Trend target: 12, Cluster target: 5

# Experiment Design

# Data-Generating Models



## Parameters

$\sigma_T$ : Variability in  $y$

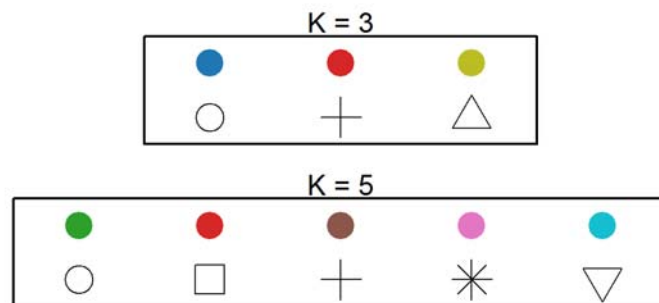
$\lambda$ : Mixing parameter

$K$ : # clusters

$\sigma_C$ : Variability around cluster centers

# Plot Aesthetic Combinations

		Trend Emphasis			
		Strength	0	1	2
Cluster Emphasis	0	Plain	Line	Line + Pred. Interval	
	1	Color Shape	Color + Line		
	2	Color + Shape Color + Ellipse		Color + Ellipse + Line + Pred. Interval	
	3	Color + Shape + Ellipse			

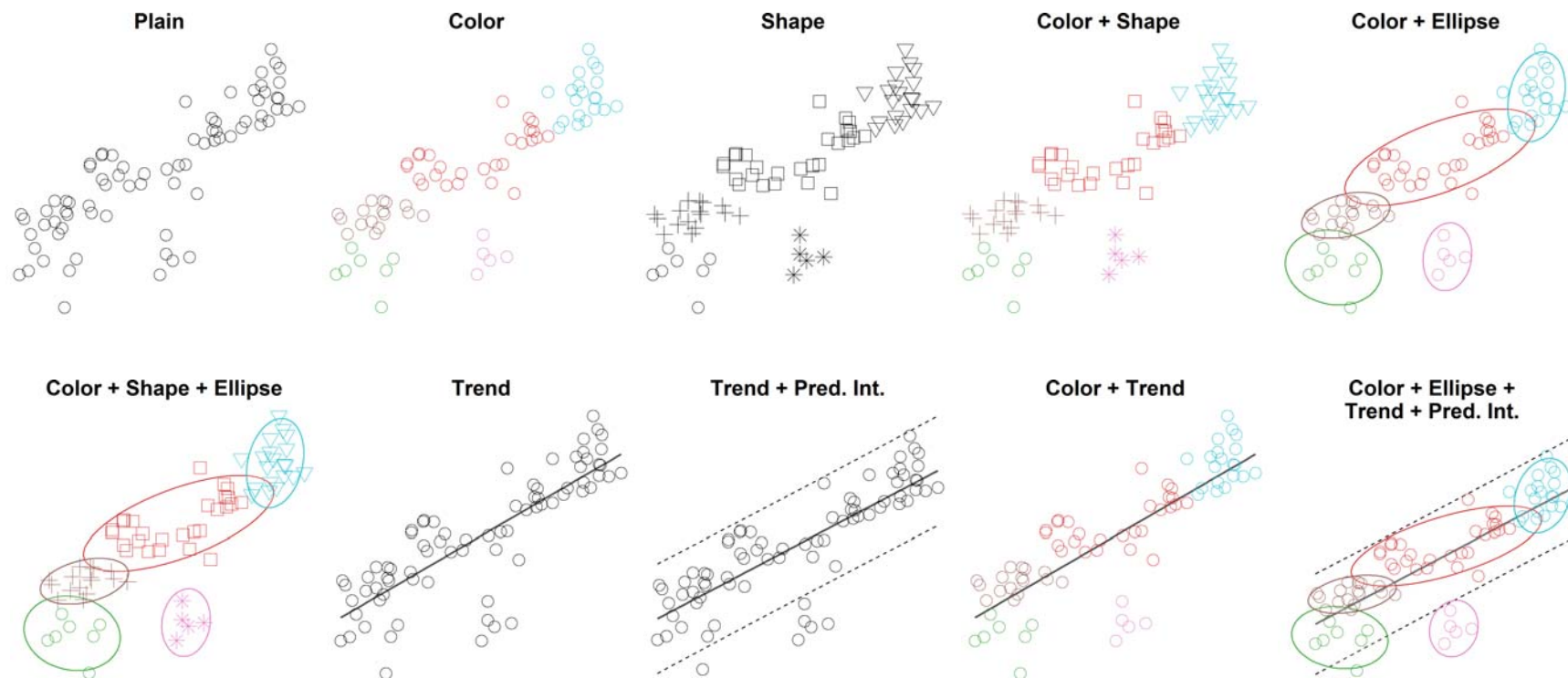


Palettes selected to provide maximum perceptual distance (Ç. Demiralp, et al., 2014).

Shapes conform to guidelines in Robinson (2003) and Lewandowsky & Spence (1989).



# Plot Aesthetic Combinations



# Experimental Structure

## Model Parameters

- Trend Strength  $\sigma_T$  = easy, med., hard
- Cluster Strength  $\sigma_C$  = easy, med., hard
- Number of Clusters  $K = 3, 5$

## Plot Aesthetics

- |                      |                   |
|----------------------|-------------------|
| • Plain              | • Color           |
| • Trend              | • Shape           |
| • Trend + Pred. Int. | • Color + Shape   |
| • Color + Trend      | • Color + Ellipse |
| • Color + Ellipse    | • Color + Shape   |
| + Trend + Pred. Int. | + Ellipse         |

## Plot Level

- 18 parameter combinations
- 3 datasets/parameter combination
- 10 plot types for each dataset  
= 540 total plots

## Evaluation Level

- Participants evaluate 10 plots:
  - 1 of each aesthetic
  - 1 of each combination of  $\sigma_T$  and  $\sigma_C$  randomized over  $K$

# Data Collection

(via Amazon Mechanical Turk)

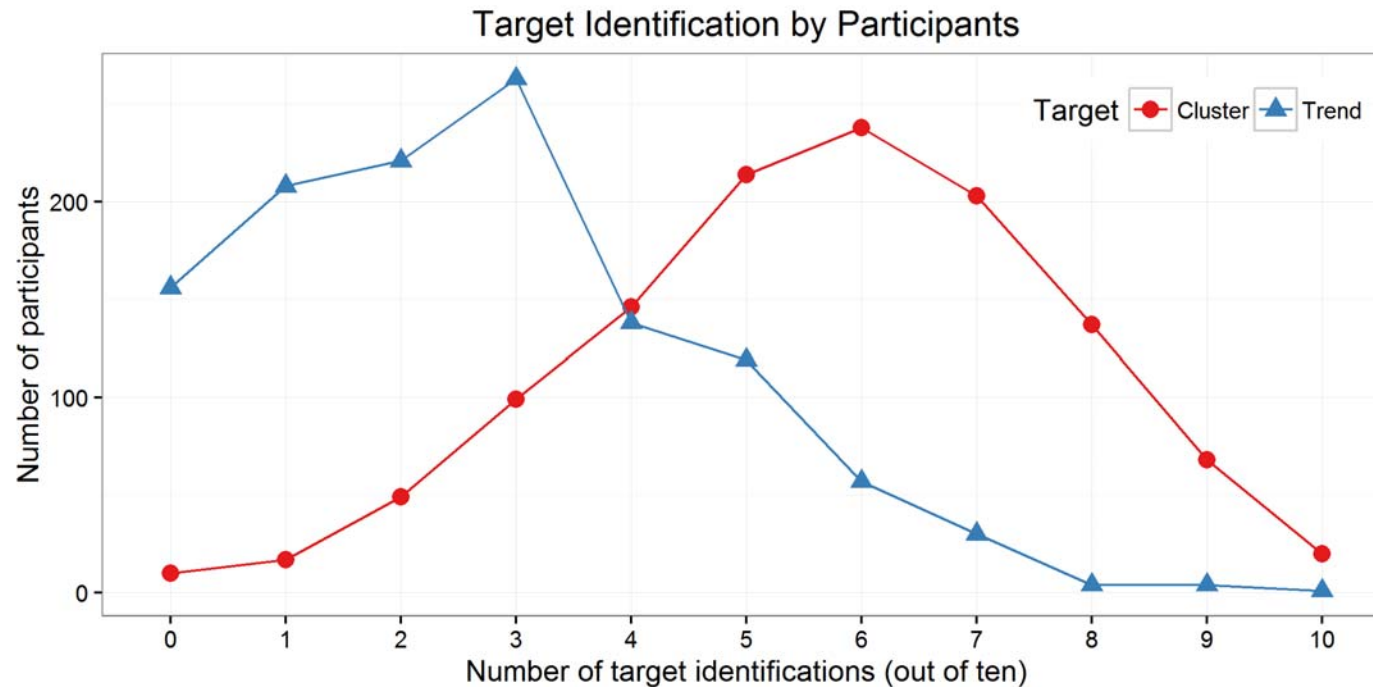
**1201** participants provided:

- Demographic information: age range, gender, education level
- 10 plot evaluations (**12010** total)
  - Target plot identification (one or more sub-plots)
  - Level of confidence in their answer (1 = least, 5=most)
  - Reasoning  
(i.e. "Strongest linear relationship", "Clustered points", "Odd shape")

# Results

- Target Identification
- Cluster vs. Trend Target Selection
- Participant Reasoning

# Target Identification



Participants selected more cluster targets than line targets.

5 plot types were expected to emphasize clustering; only 2 plot types were expected to emphasize trends.

# Faceoff: Cluster vs. Trend?

# Cluster vs. Trend

Define  $C_{ijk}$  to be the event

{Participant  $k$  selects the  
cluster target for dataset  $j$   
with aesthetic set  $i$ },

and  $T_{ijk}$  to be the analogous selection of the trend target.

$$\text{logit } P(C_{ijk} | C_{ijk} \cup T_{ijk}) = \mathbf{W}\alpha + \mathbf{X}\beta + \mathbf{J}\gamma + \mathbf{K}\eta$$

# Cluster vs. Trend

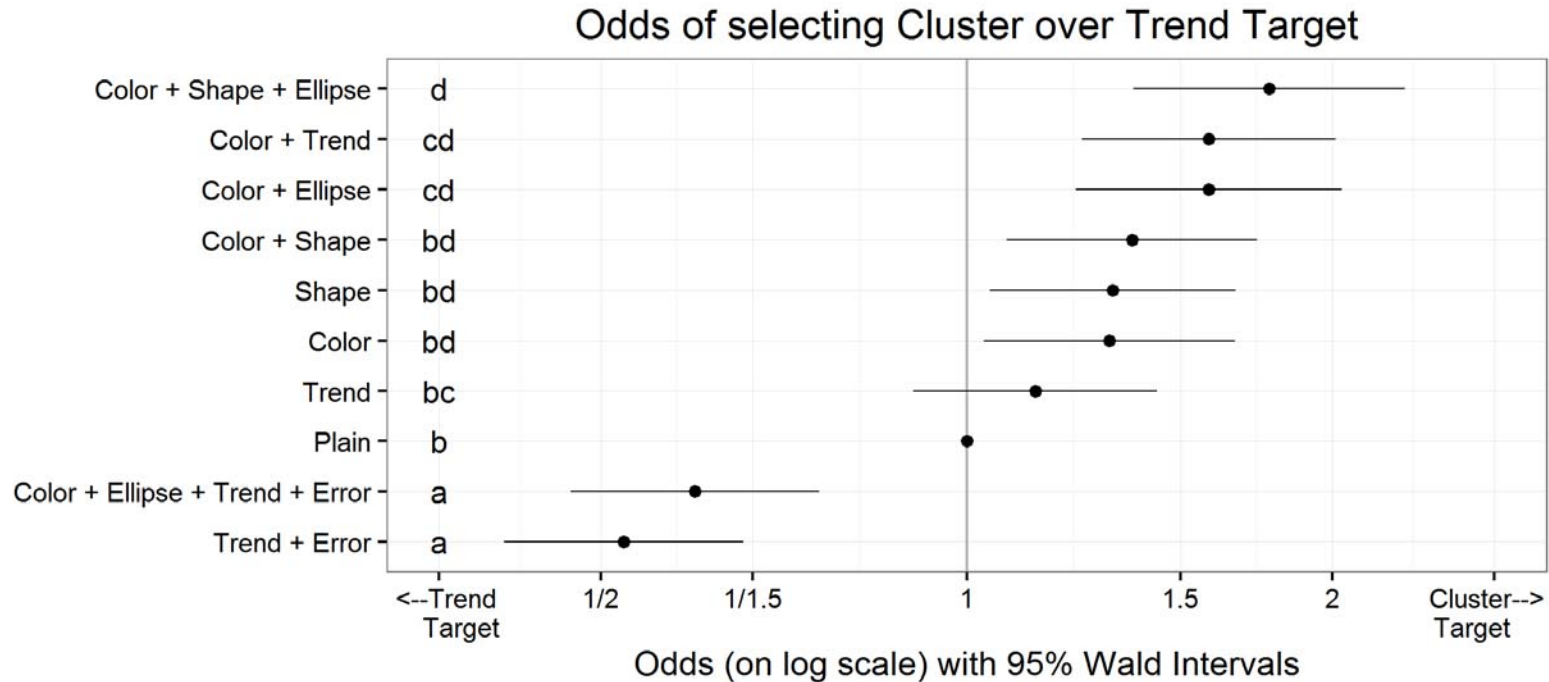
Given that participants identified one of the two target plots...

$\alpha$	data model fixed effects
$\beta$	effect of specific plot types
$\gamma_j \stackrel{iid}{\sim} N(0, \sigma_{\text{dataset}}^2)$	Dataset random effects
$\eta_k \stackrel{iid}{\sim} N(0, \sigma_{\text{participant}}^2)$	Participant random effects
$\epsilon_{ijk} \stackrel{iid}{\sim} N(0, \sigma_e^2)$	Individual evaluation errors

Dataset and participant effects are orthogonal by design



# Cluster vs. Trend



Plot types are significantly different if they do not share a letter

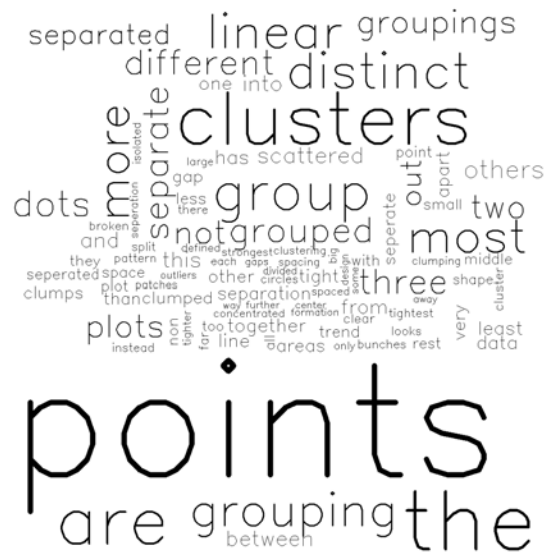
Participants are **0.52** times as likely to select cluster targets when plots have trend line and prediction interval aesthetics.

Participants are **1.77** times as likely to select cluster targets when plots have color, shape, and ellipse aesthetics.

# Participant Reasoning

# Participant Reasoning

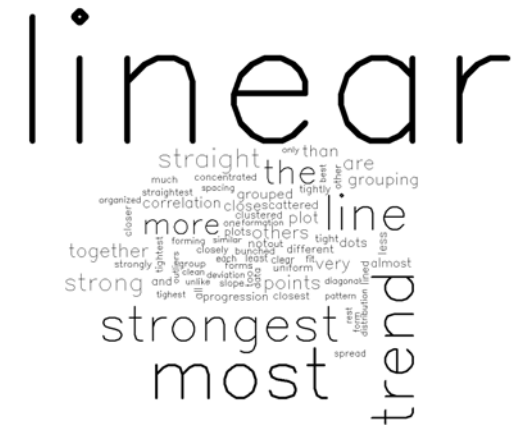
## Plain Plots



Neither Target  
(N=127)



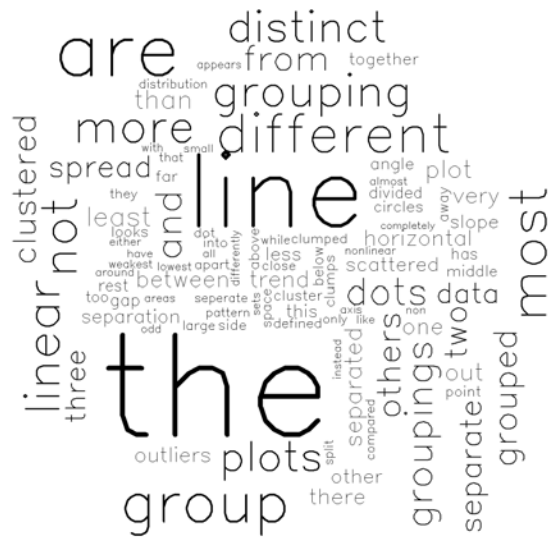
## Cluster Target (N=712)



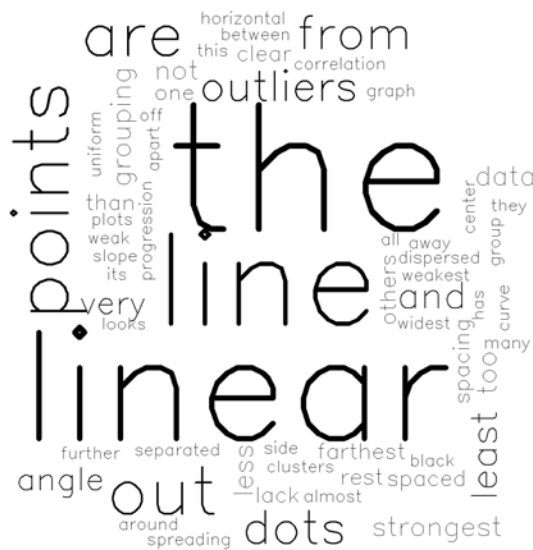
## Trend Target (N=355)

# Participant Reasoning

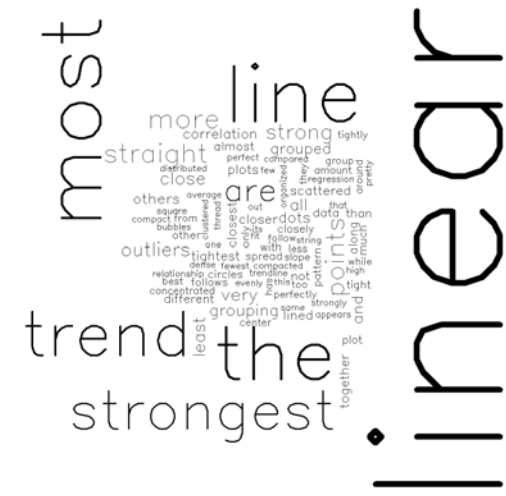
## Trend line



Neither Target  
(N=159)



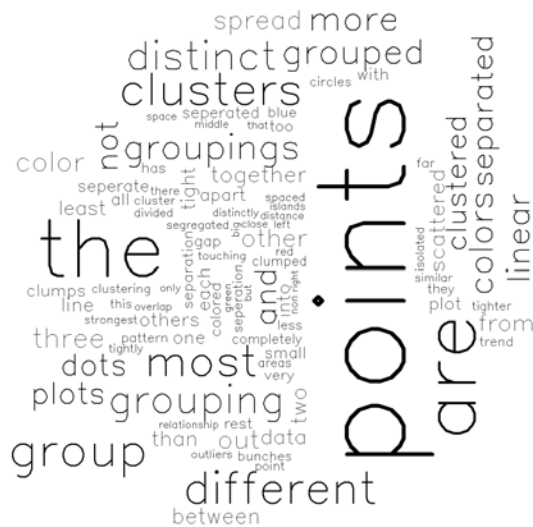
Cluster Target  
(N=694)



Trend Target  
(N=333)

# Participant Reasoning

## Color Plots



Neither Target  
(N=188)



Cluster Target  
(N=715)



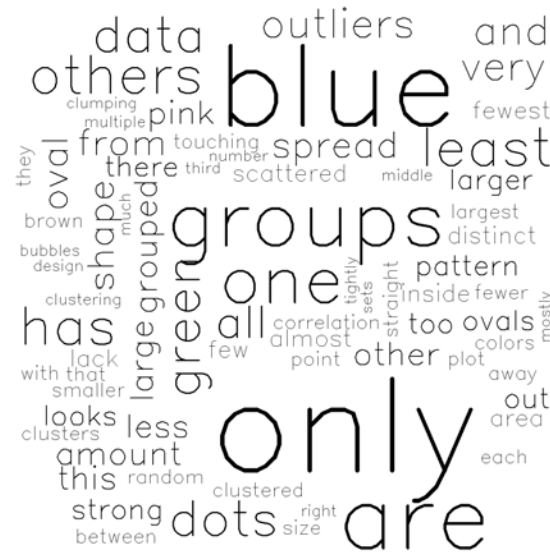
## Trend Target (N=292)

# Participant Reasoning

## Color + Ellipse Plots



Neither Target  
(N=347)



Cluster Target  
(N=621)



## Trend Target (N=222)

# Discussion

# Conclusions

- Plot aesthetics influence perception of ambiguous data displays
- Aesthetic effects are not additive:  
Conflict conditions don't show similar/neutral results
- Aesthetics which recruit new gestalt heuristics have more influence,  
and we can quantify the size of that influence



# More Information

- Github Repository (Data, paper, code)  
<http://github.com/srvanderplas/FeatureHierarchy/>
- JCGS Paper: Clusters Beat Trend!? Testing Feature Hierarchy in Statistical Graphics  
<http://www.tandfonline.com/doi/abs/10.1080/10618600.2016.1209116>
  - Lots of models examining trial completion time, parameter strength, and participant confidence
  - Much more in-depth treatment of gestalt perception
  - Simulation-based modeling of null plot characteristics

# Future Work

- Restrict group sizes so null plots have the same objects as target plots
- Explore the effect of different types of common region for error bands and ellipses - shading, bounding boxes, etc.
- Test ellipse and error band aesthetics alone and with trend lines and color to examine interaction effects
- Test plotted statistics (trend line, ellipses, error bands) with and without data points to examine interactions between heuristics from the data and heuristics from summary statistics