Learning Perceptual Kernels for Visualization Design

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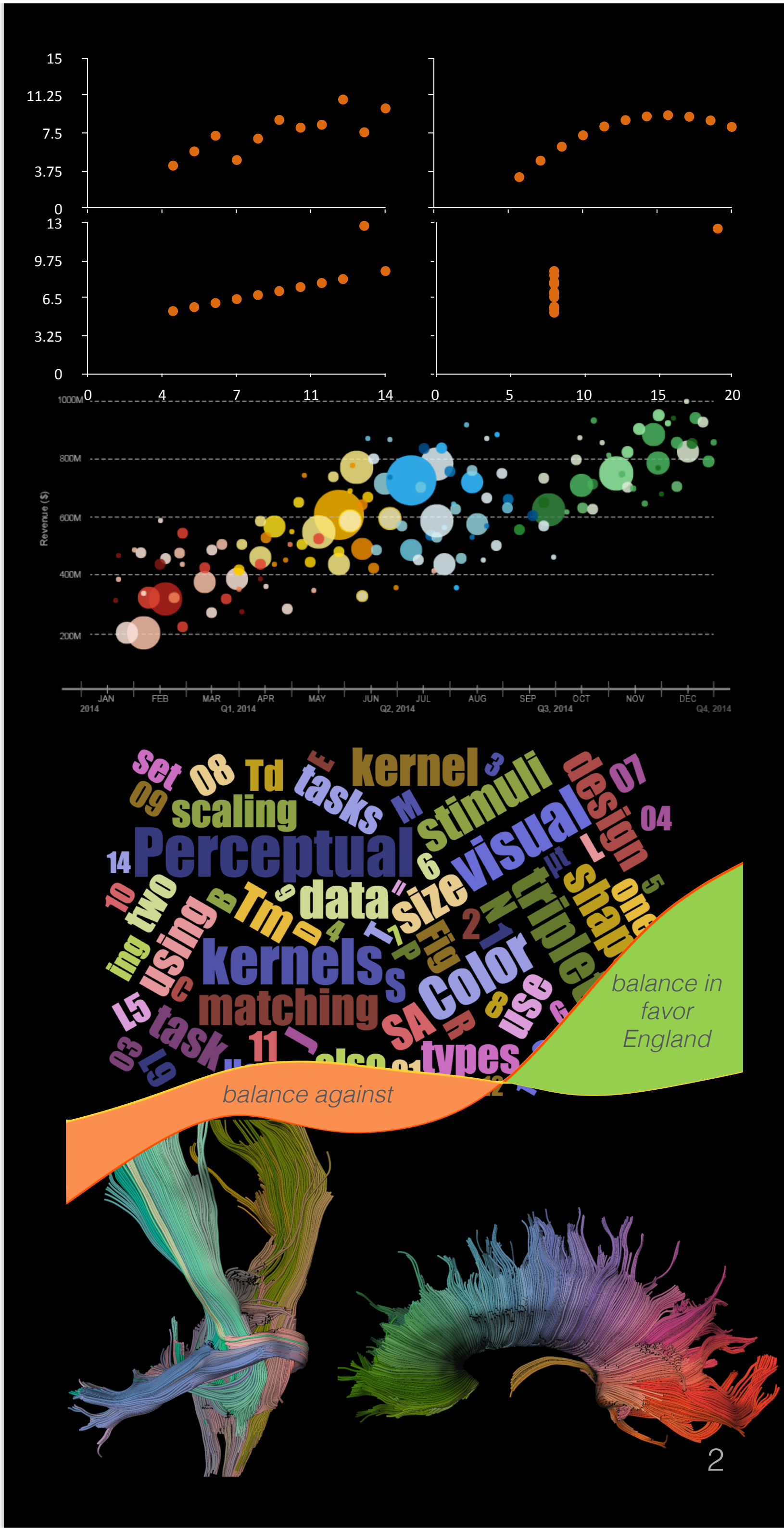
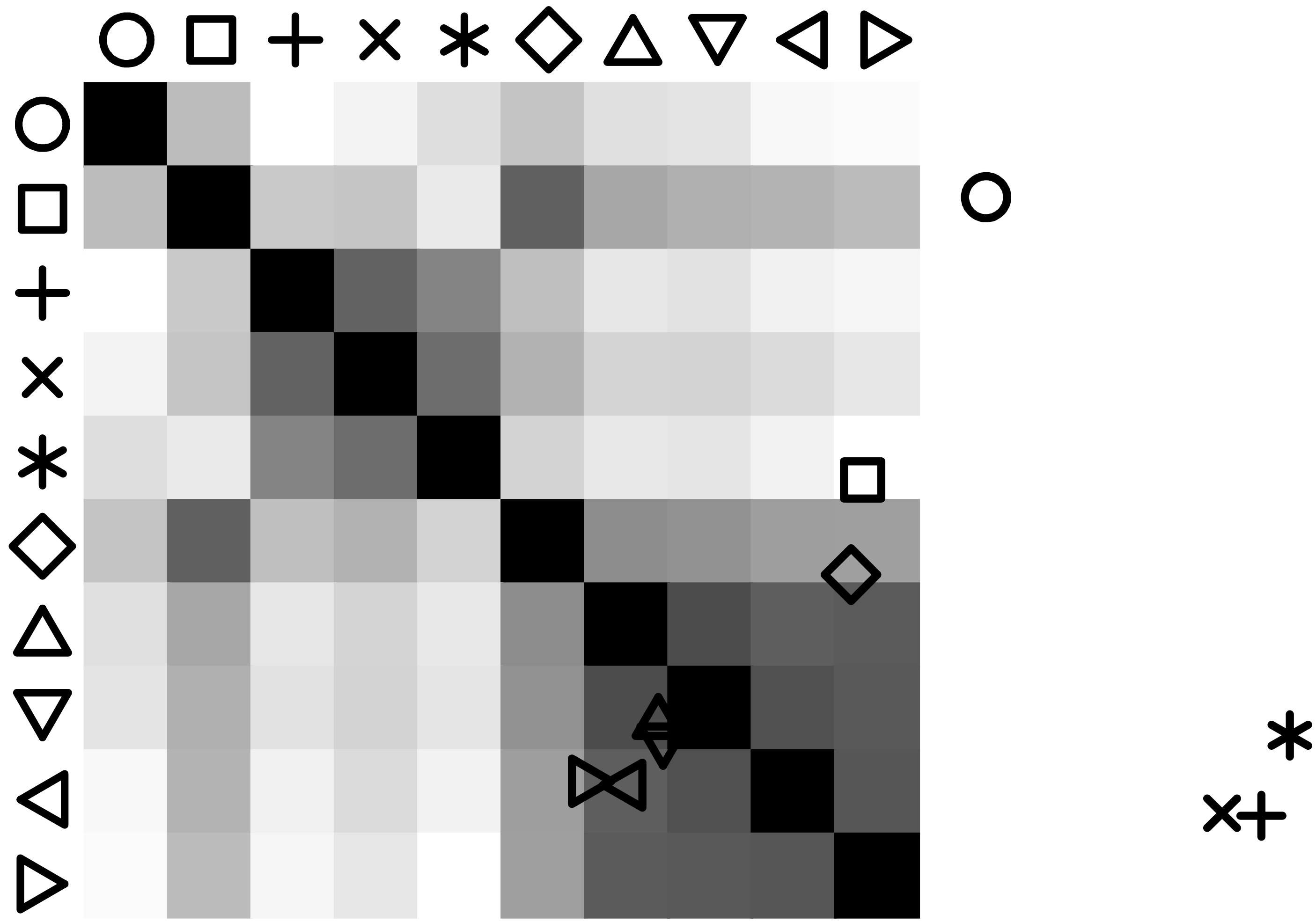
Visualizations Leverage Perception



Engineering Perception Into Visualization Design?

A Measure of Perceptual Reality

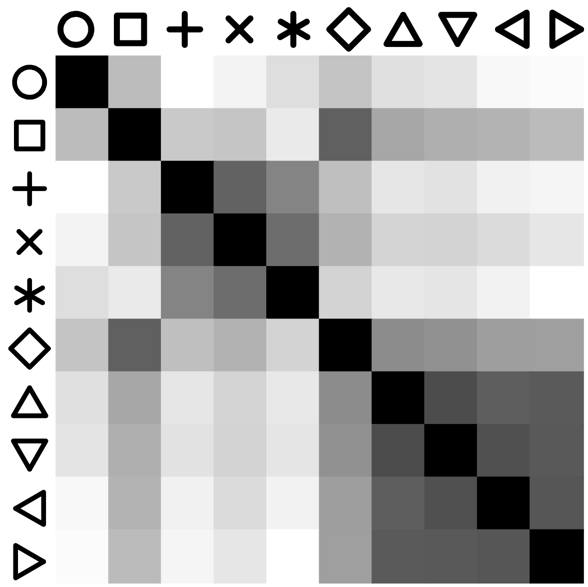


Perceptual Kernel 2D Projection

What are Perceptual Kernels Useful For?

Automating Visualizations

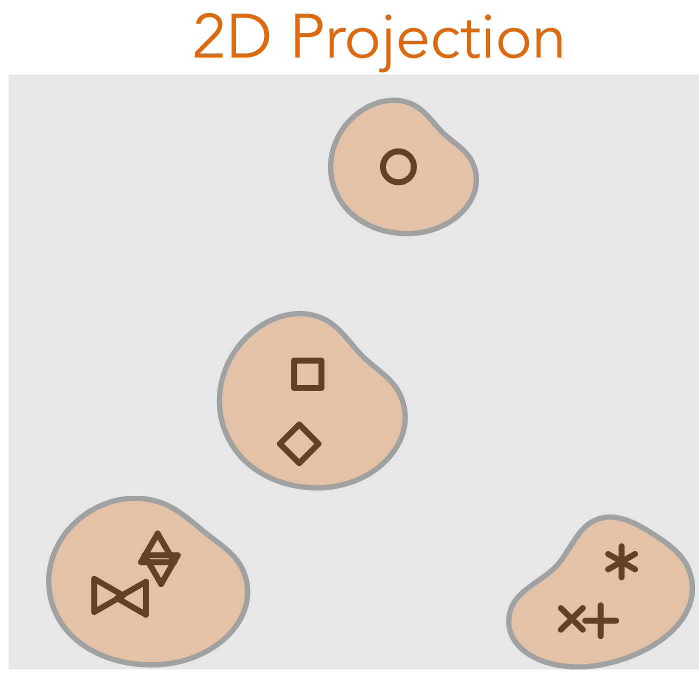
Palette Design



Palette Design

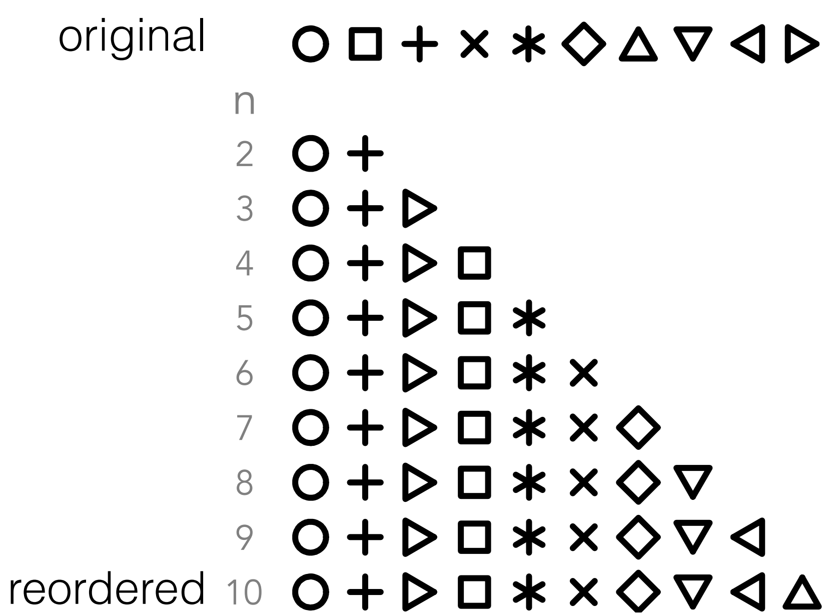
original		○ □ + × ∗ ◇ △ ▽ ◁ ▷
	n	
	2	○ +
	3	○ + ▷
	4	○ + ▷ □
	5	○ + ▷ □ ∗
	6	○ + ▷ □ ∗ ×
	7	○ + ▷ □ ∗ × ◇
	8	○ + ▷ □ ∗ × ◇ ▽
	9	○ + ▷ □ ∗ × ◇ ▽ ◁
reordered	10	○ + ▷ □ ∗ × ◇ ▽ ◁ △

Palette Design

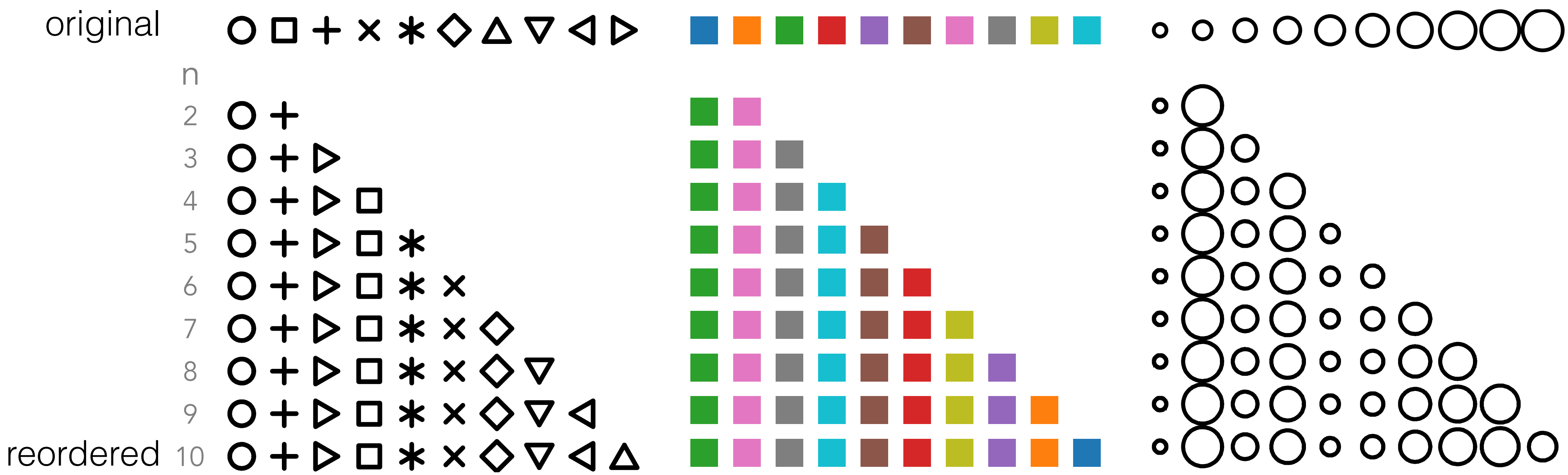


reordered ○ + ▷ □ ✱ × ◇ ▽ ◁ △

Palette Design



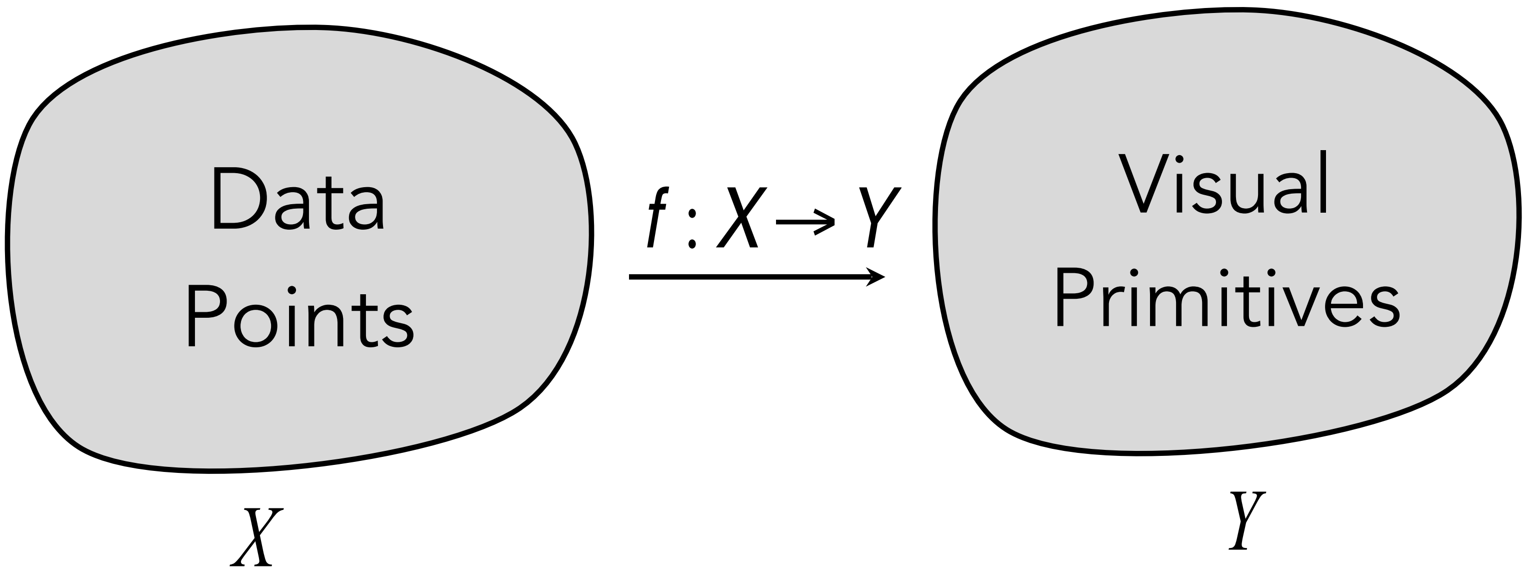
Palette Design



Palettes re-ordered to maximize perceptual discriminability

Visual Embedding: A Model for Visualization

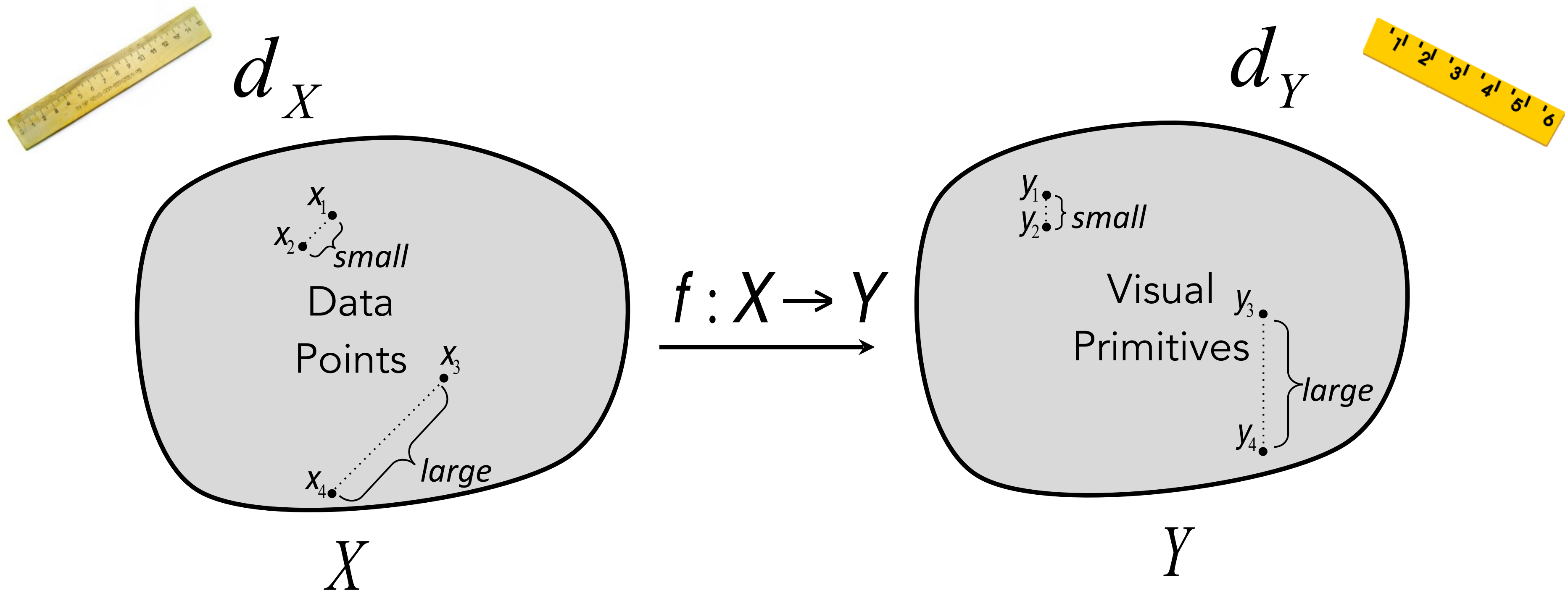
Visualizations as Functions



quantitative
ordinal
nominal
…

color
size
shape
orientation
texture
…

Visual Embedding



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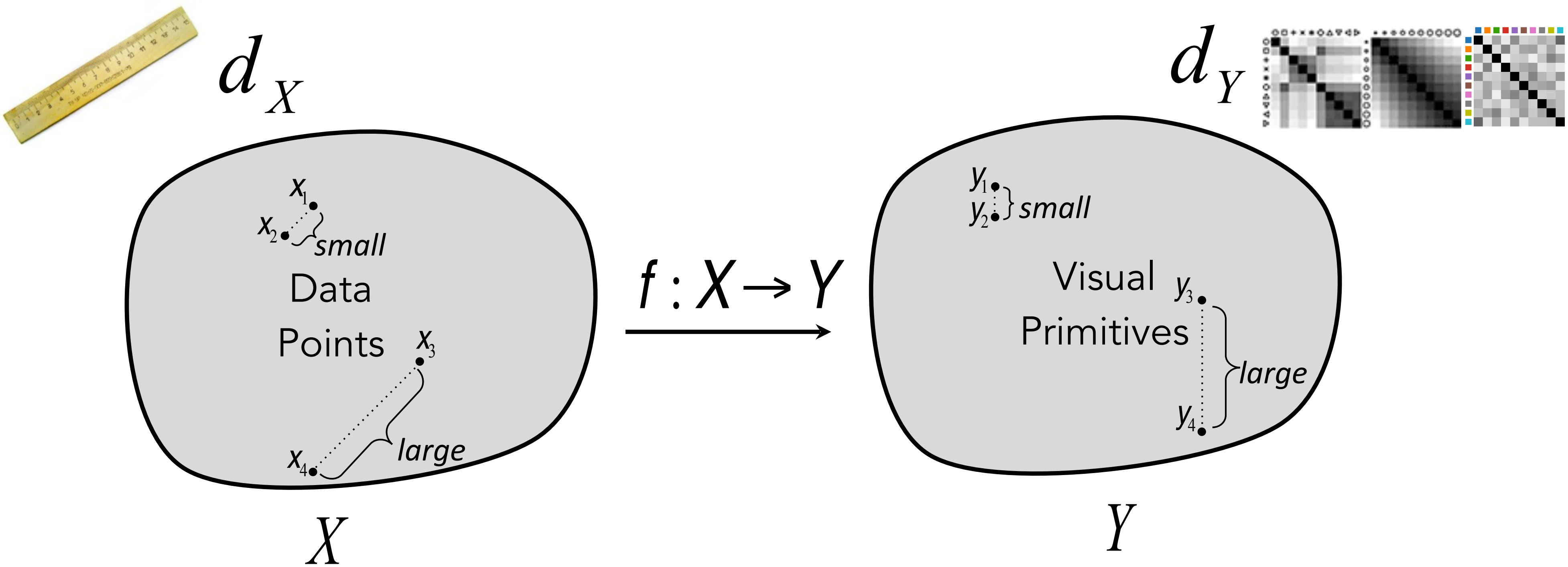

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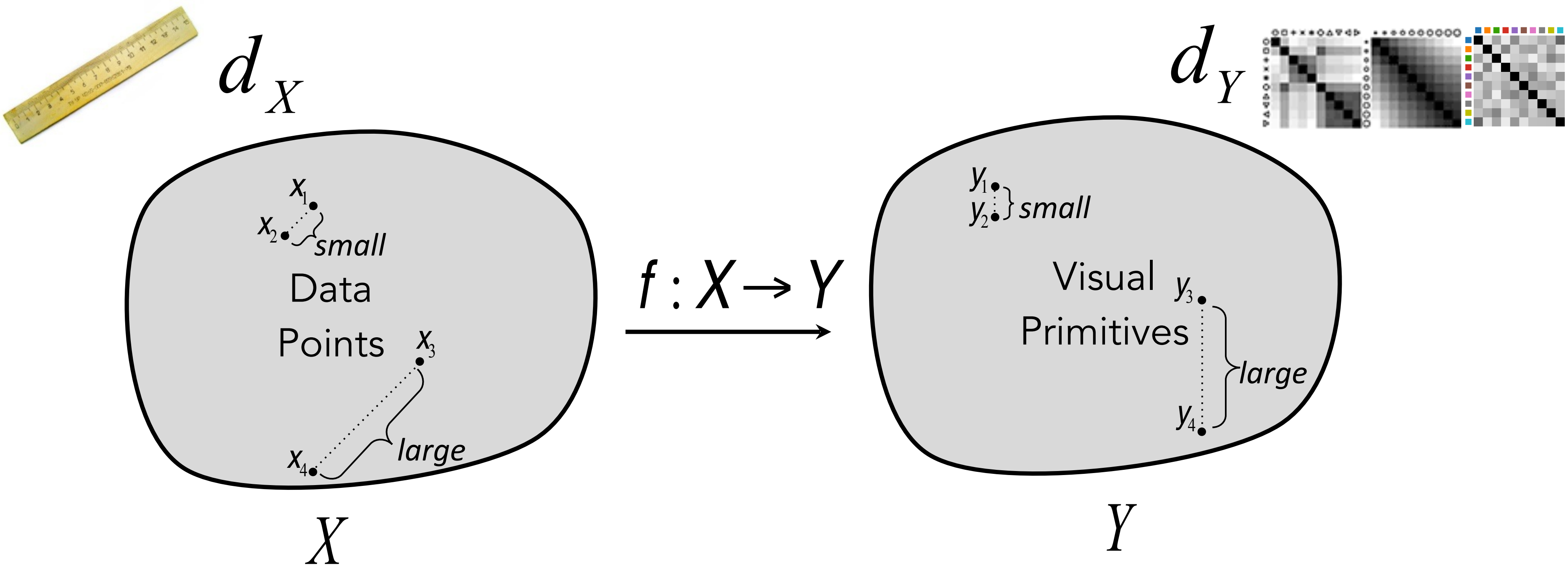
Visual Embedding

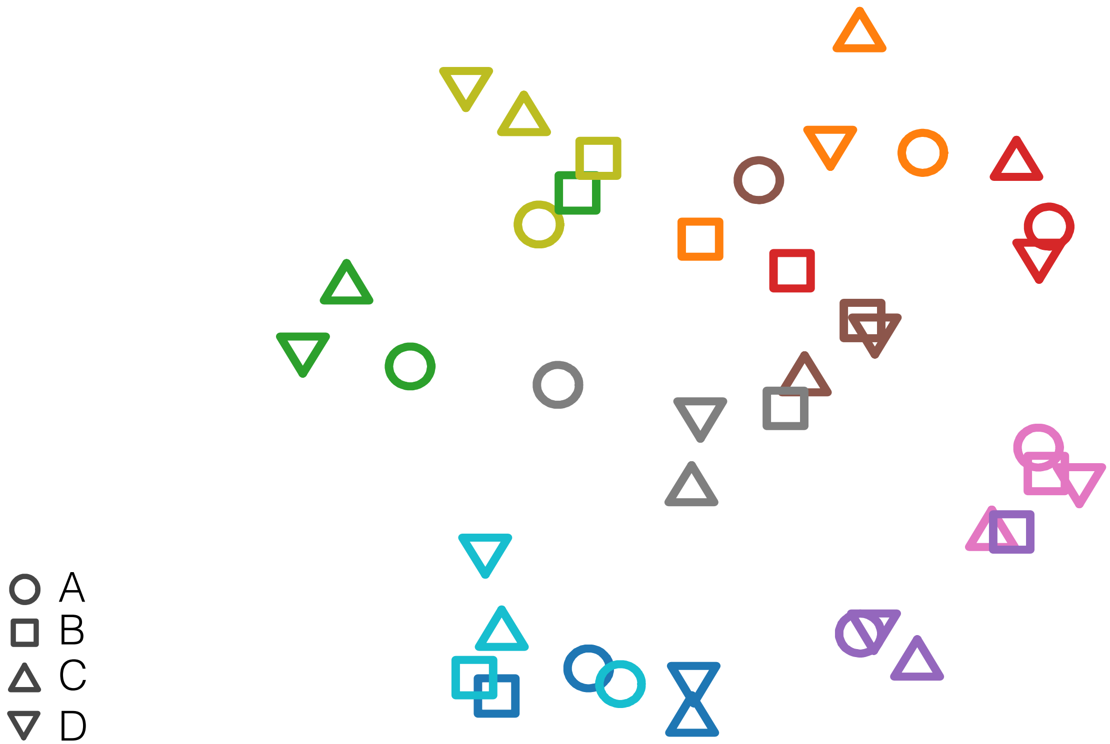


quantitative
ordinal
nominal
…

color
size
shape
orientation
texture
…

NOT NEED TO BE METRIC

Rank Correlations



	A	B	C	D
A	1.00	0.75	0.67	0.59
B		1.00	0.81	0.77
C			1.00	0.87
D				1.00

Rank Correlations

○ A
□ B
△ C
▽ D

	A	B	C	D
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B		1.00	0.81	0.77
C			1.00	0.87
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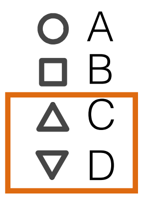
Rank Correlations



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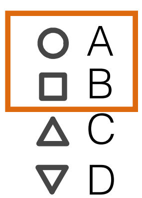

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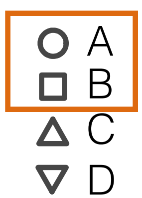

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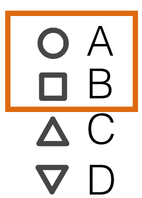

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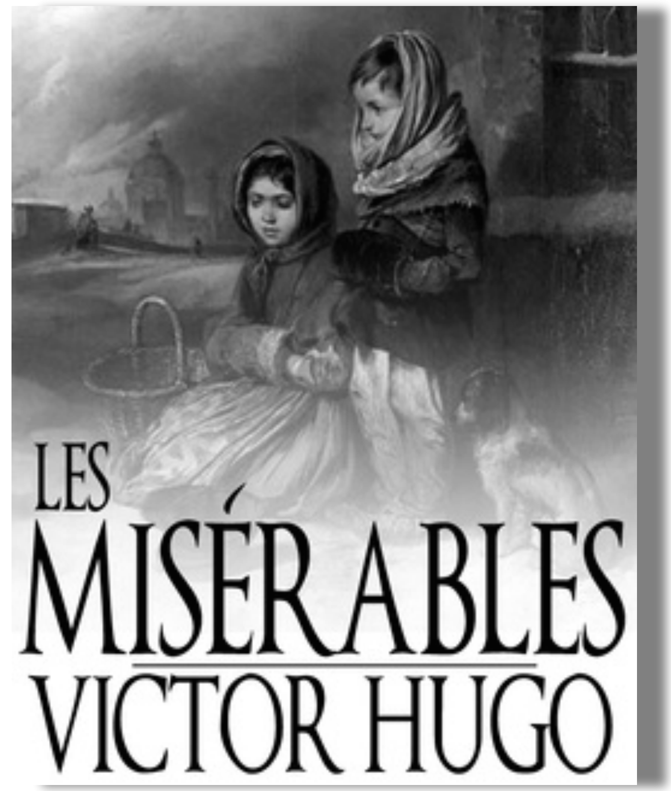
C			1.00	0.87
D				1.00

Cluster Connectivity

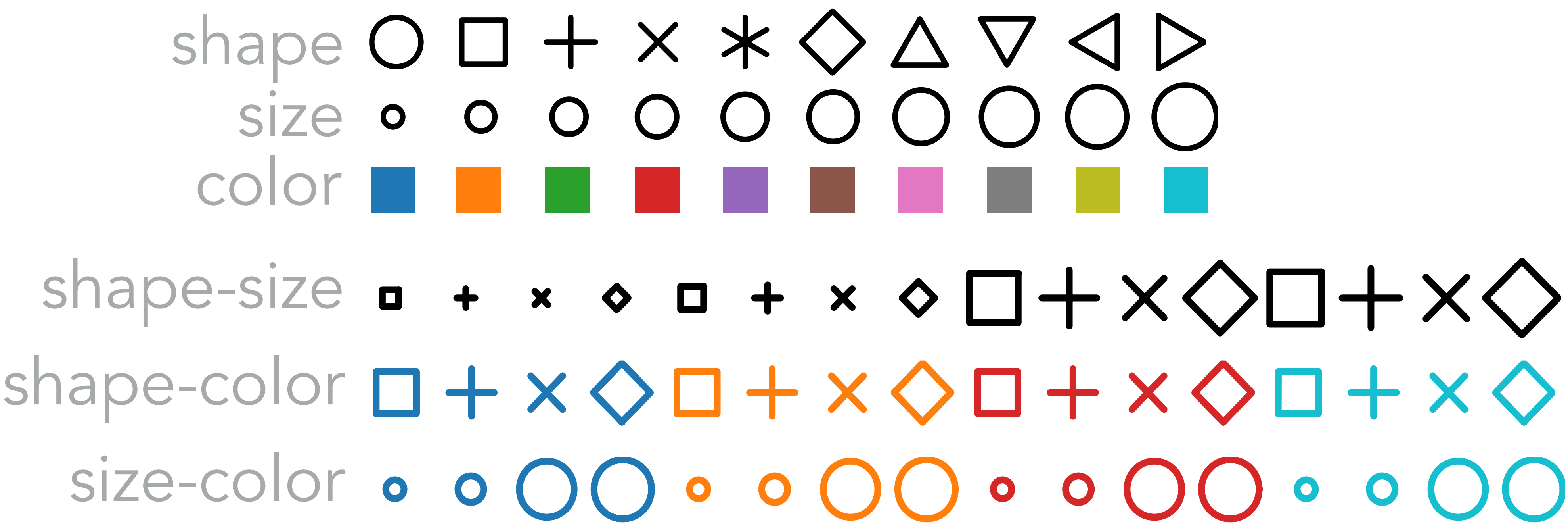
Encode community clusters in a character co-occurrence graph.



CONTRIBUTIONS

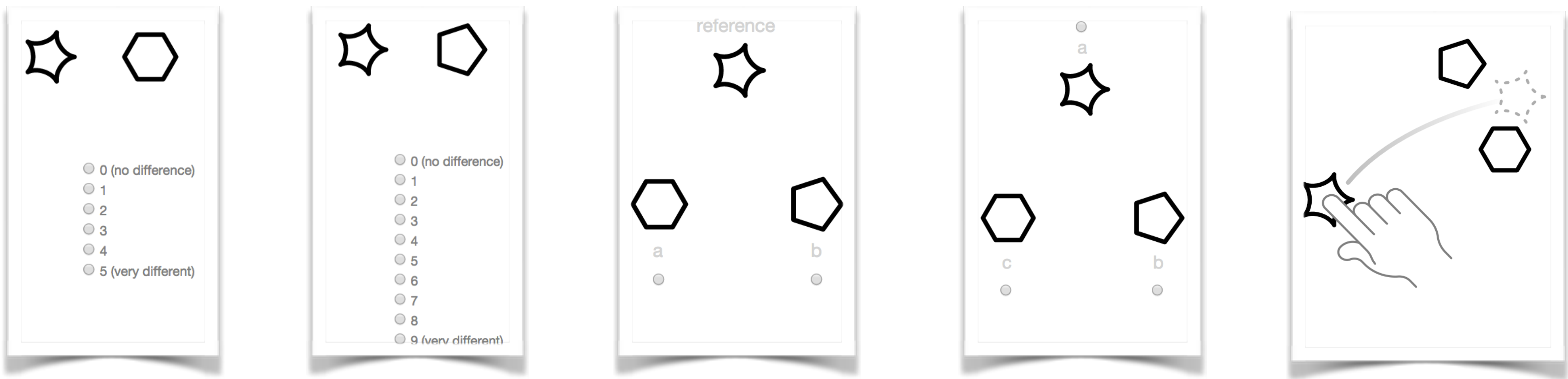
CONTRIBUTIONS

1) Estimate perceptual kernels



CONTRIBUTIONS

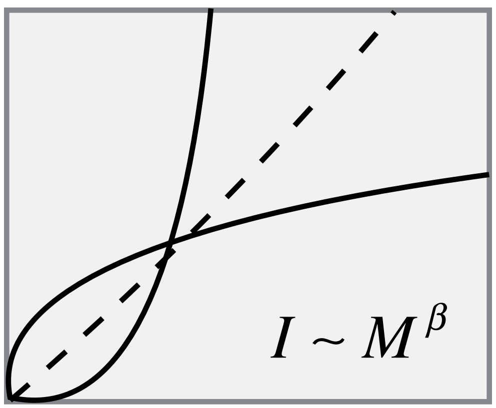
2) Compare alternative judgment types



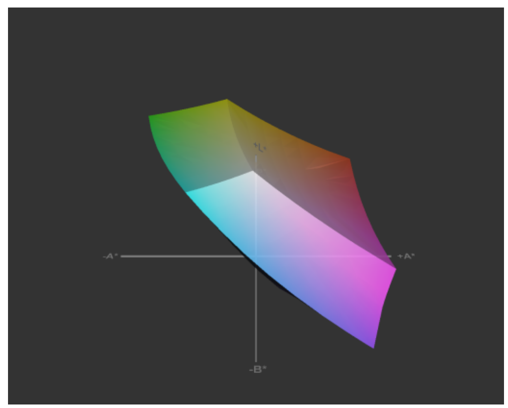
pairwise-5 | pairwise-9 | triplet matching | triplet discrimination | manual

CONTRIBUTIONS

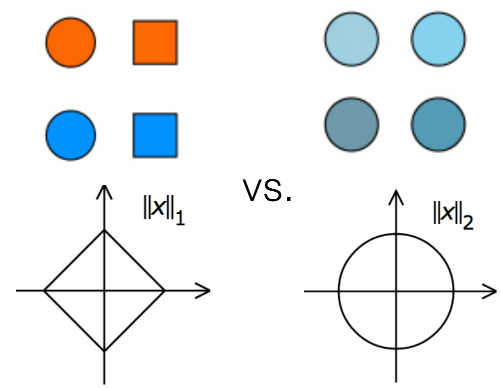
3) Assess using existing models



Stevens' Power Law



CIELAB
CIEDE2000
Color Names

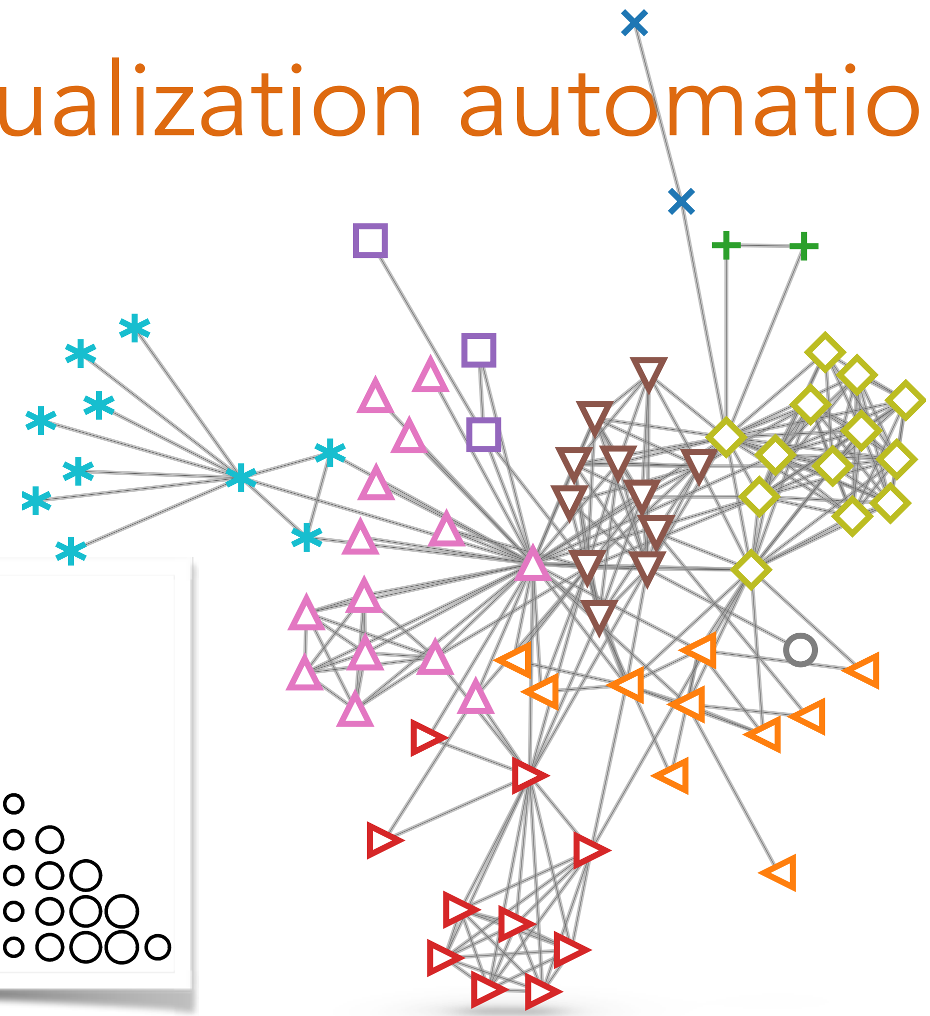


Garner's Integrality

CONTRIBUTIONS

4) Demonstrate in visualization automation

designing palettes



visual embedding

Crowd-sourcing Perceptual Kernels

Study Overview

Variables

shape · size · color · shape-size · shape-color · size-color

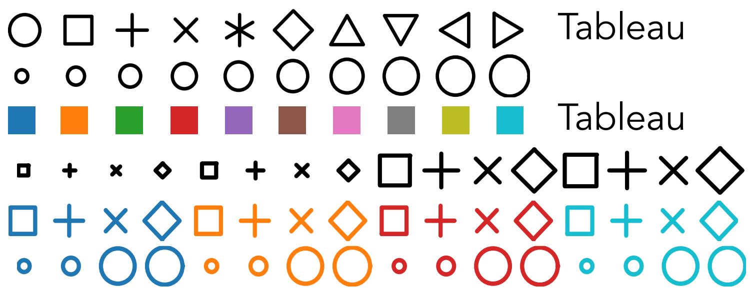
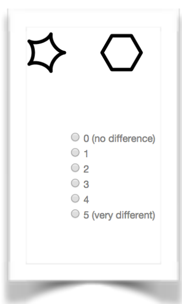


Tableau (shape)

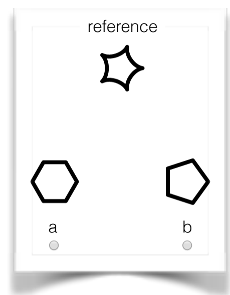
Tableau (color)

Tasks

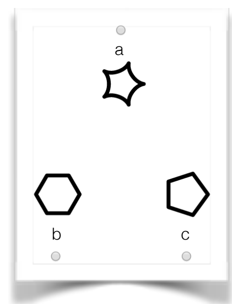


pairwise-5
L5

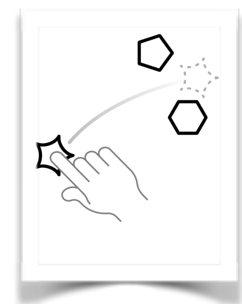
pairwise-9
L9



triplet matching
Tm



triplet discrimination
Td



manual spatial arrangement
SA

Subjects

600 Turkers based in the US

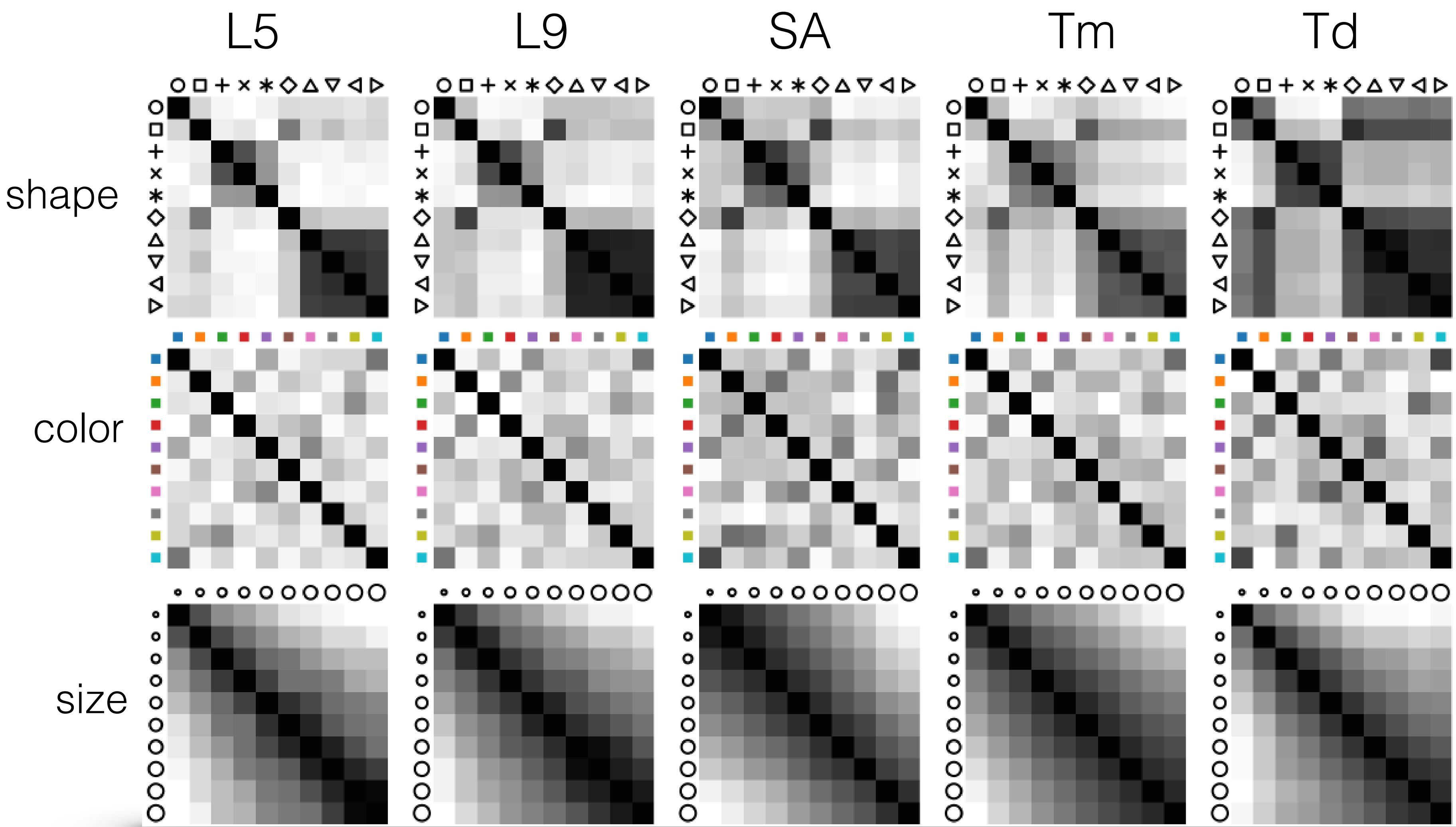
95% approval rate

minimum 100 approved HITs

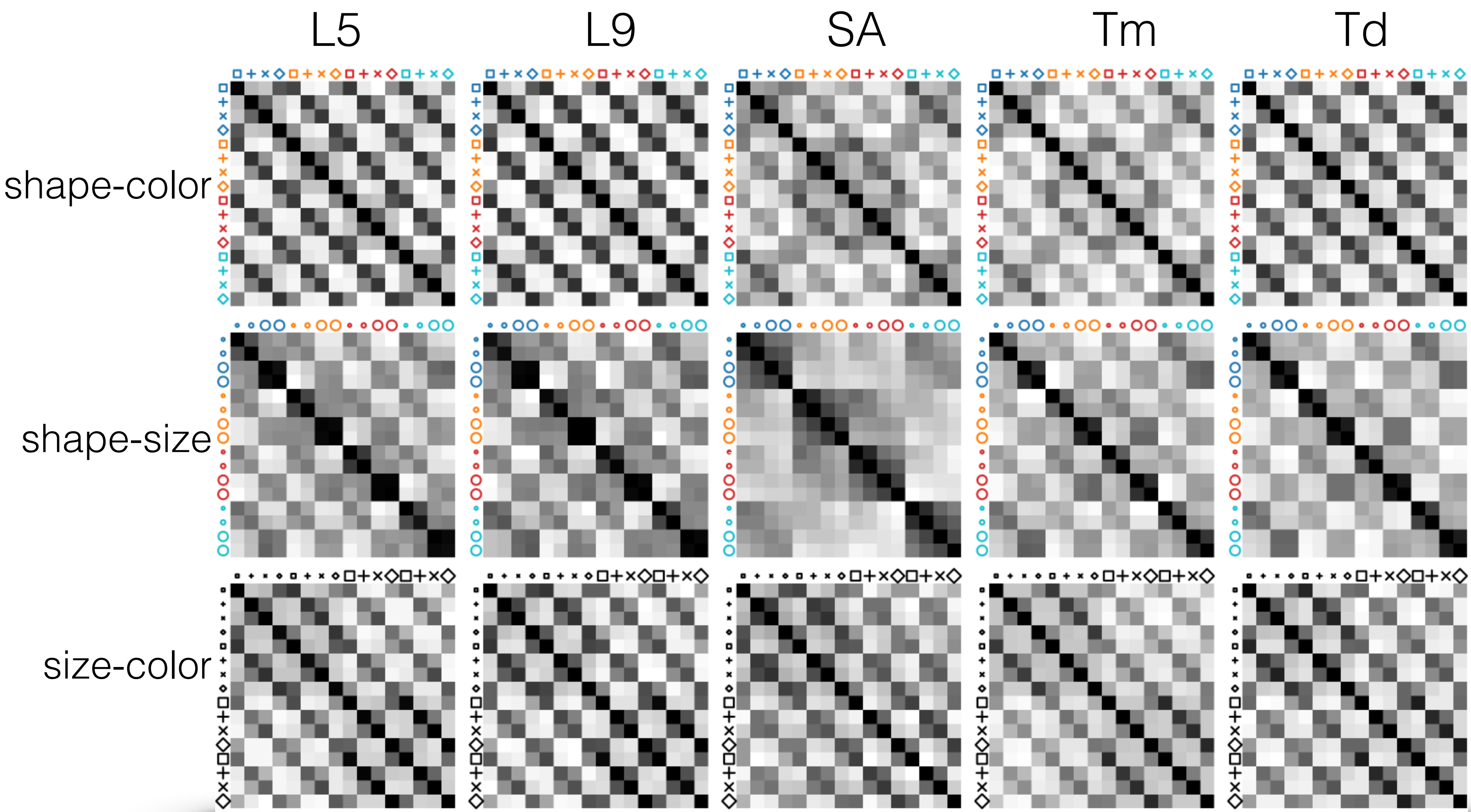
Platform

amazon mechanical turk beta

Univariate Perceptual Kernels



Bivariate Perceptual Kernels

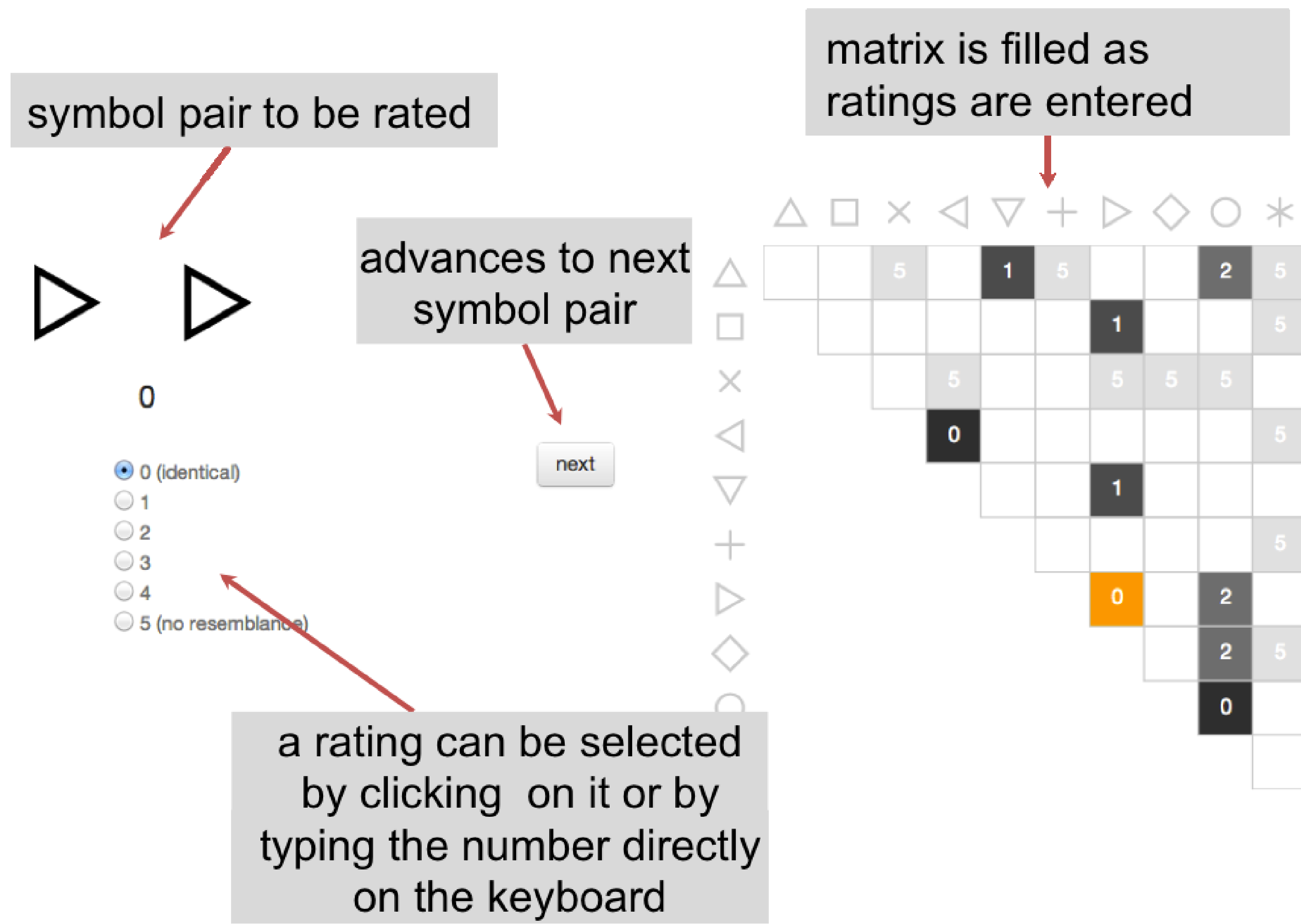


Judgment Tasks

1. Pairwise rating on 5-point scale (L5)
2. Pairwise rating on 9-point scale (L9)
3. Triplet ranking with matching (Tm)
4. Triplet ranking with discrimination (Td)
5. Spatial arrangement (SA)

Judgment Tasks

1. Pairwise rating on 5-point scale (L5)



Judgment Tasks

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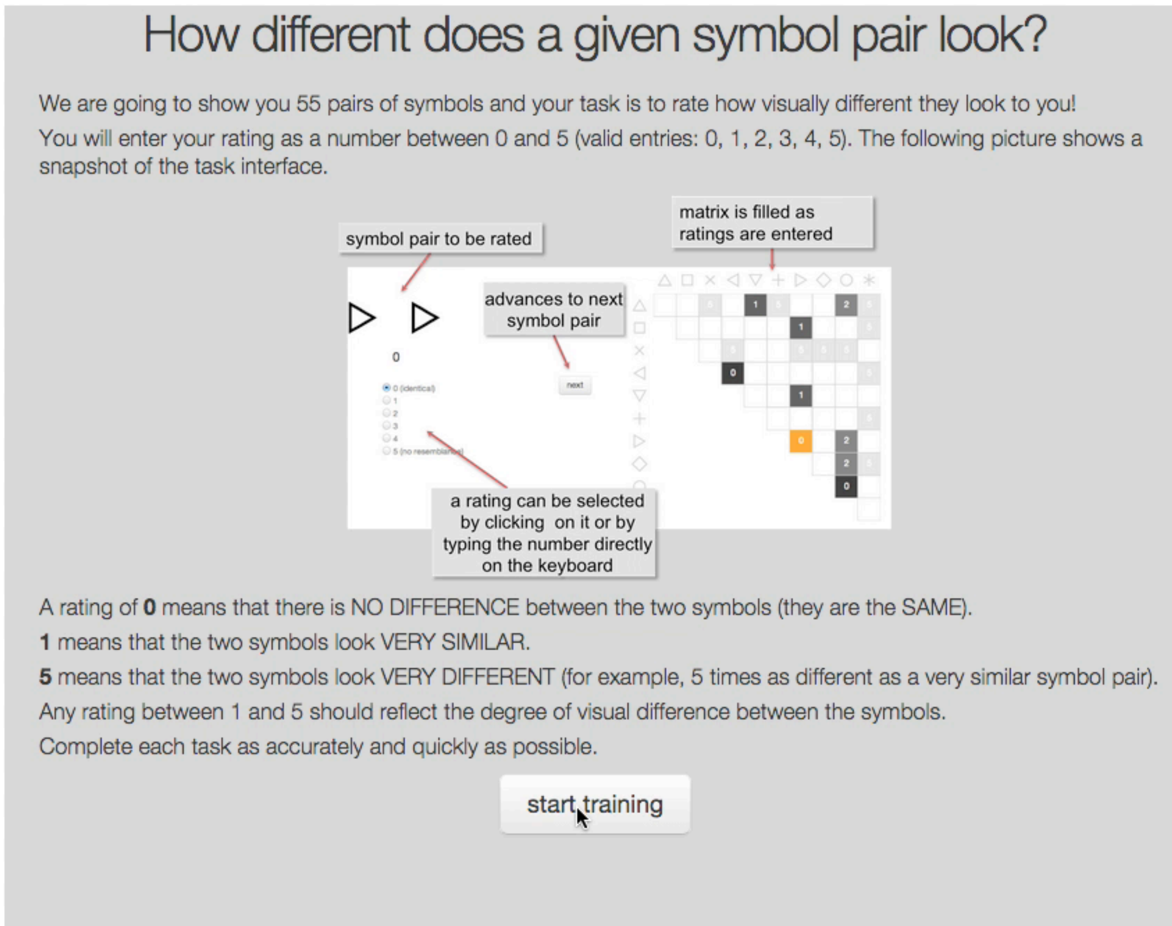
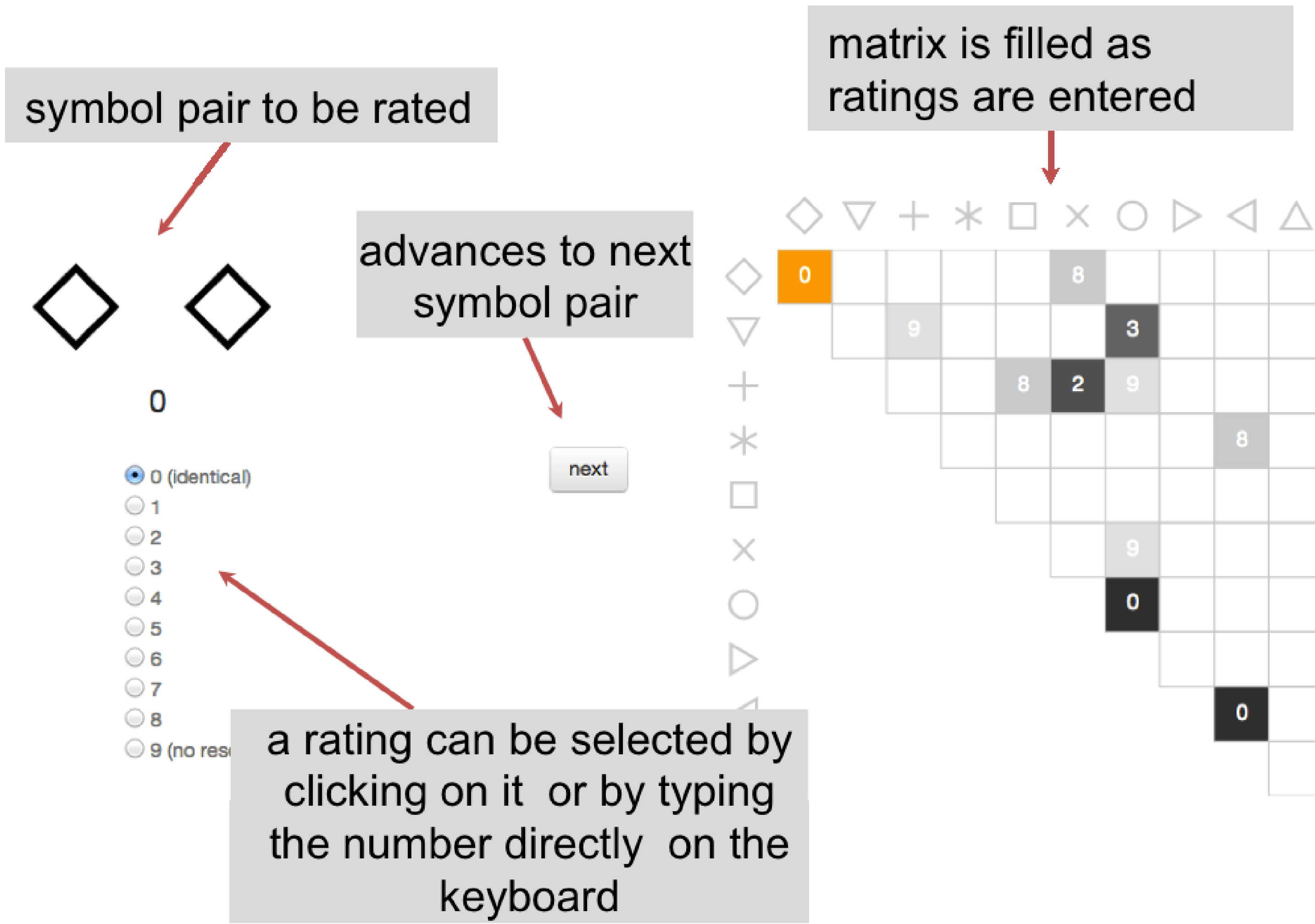


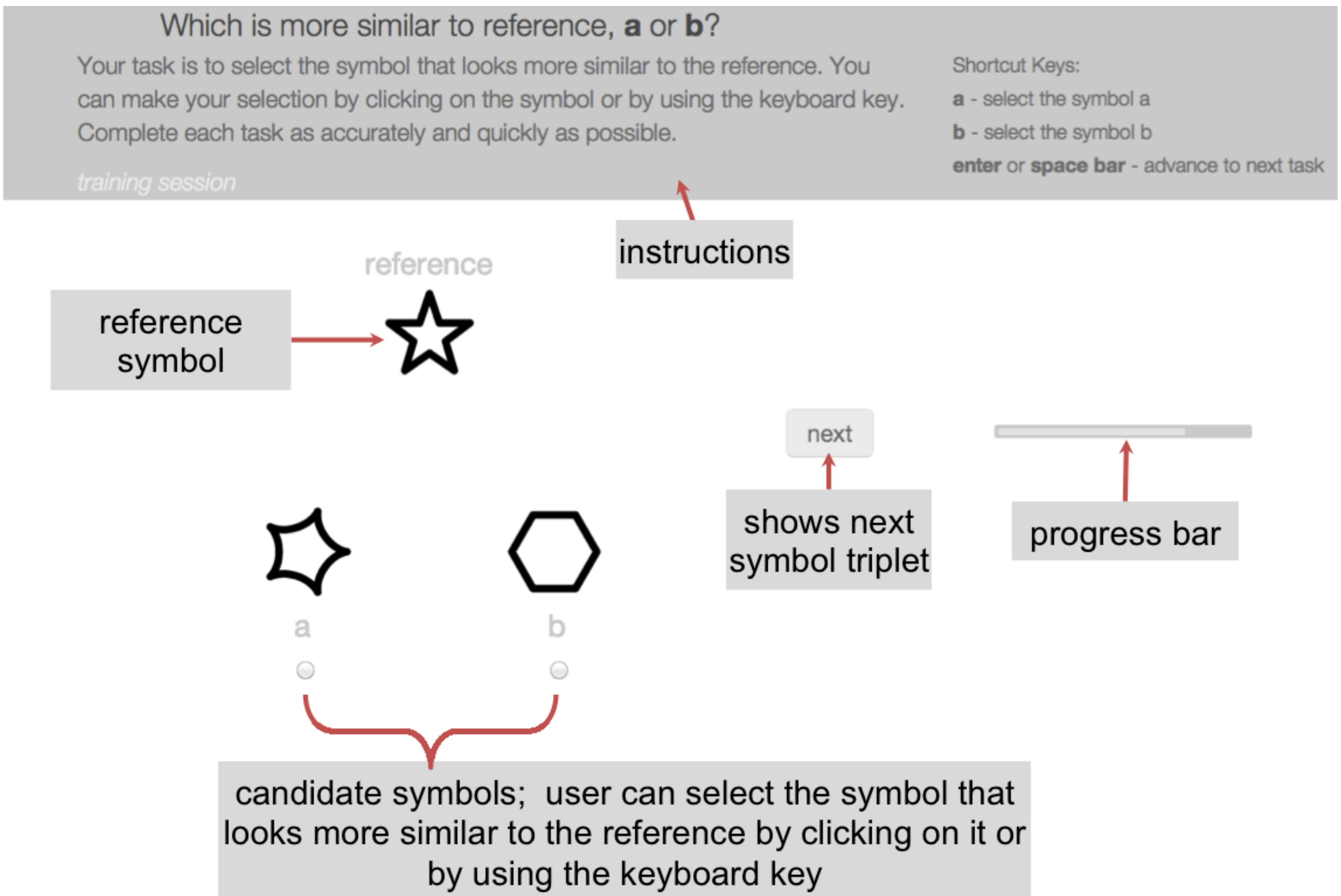
Judgment Tasks

2. Pairwise rating on 9-point scale (L9)



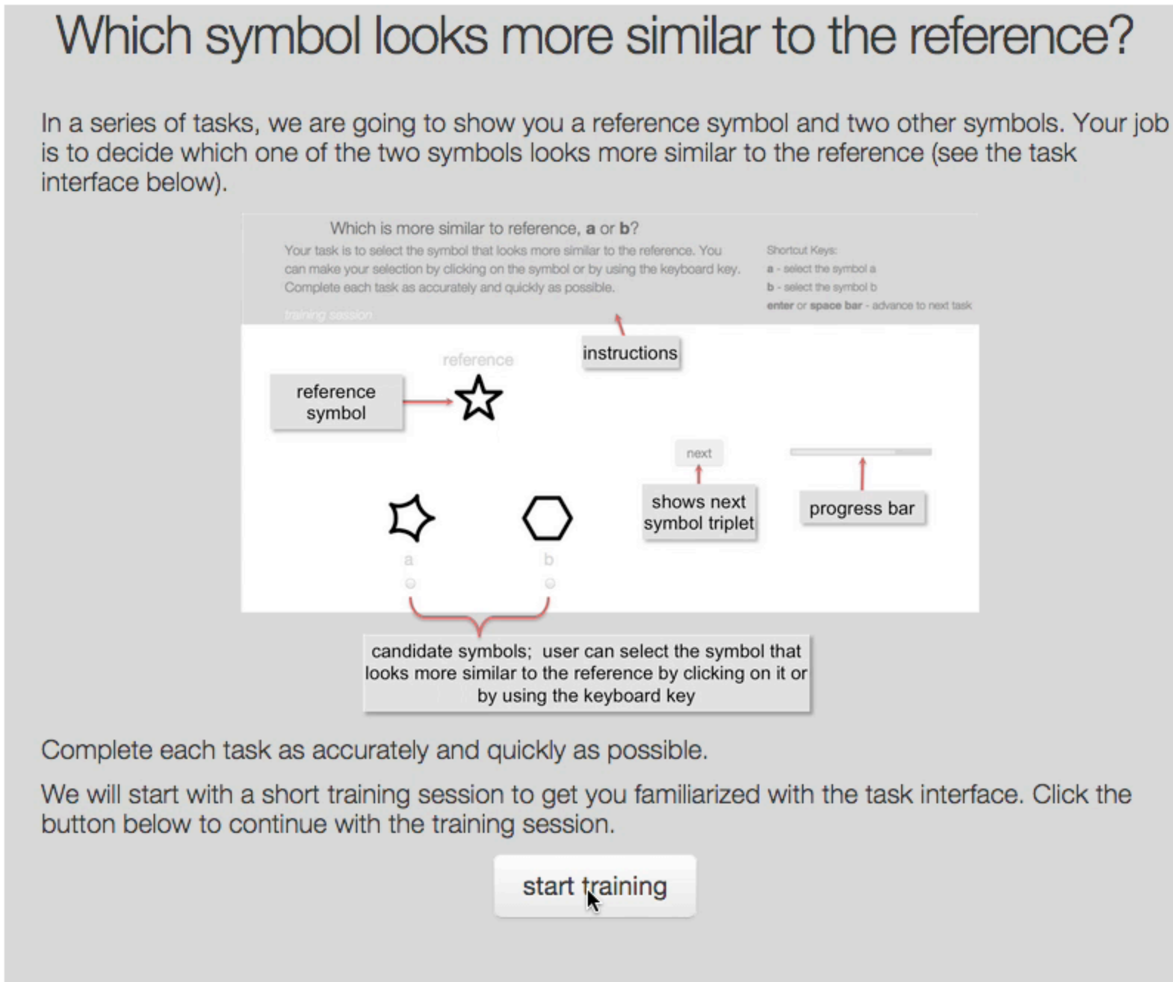
Judgment Tasks

3. Triplet ranking with matching (Tm)



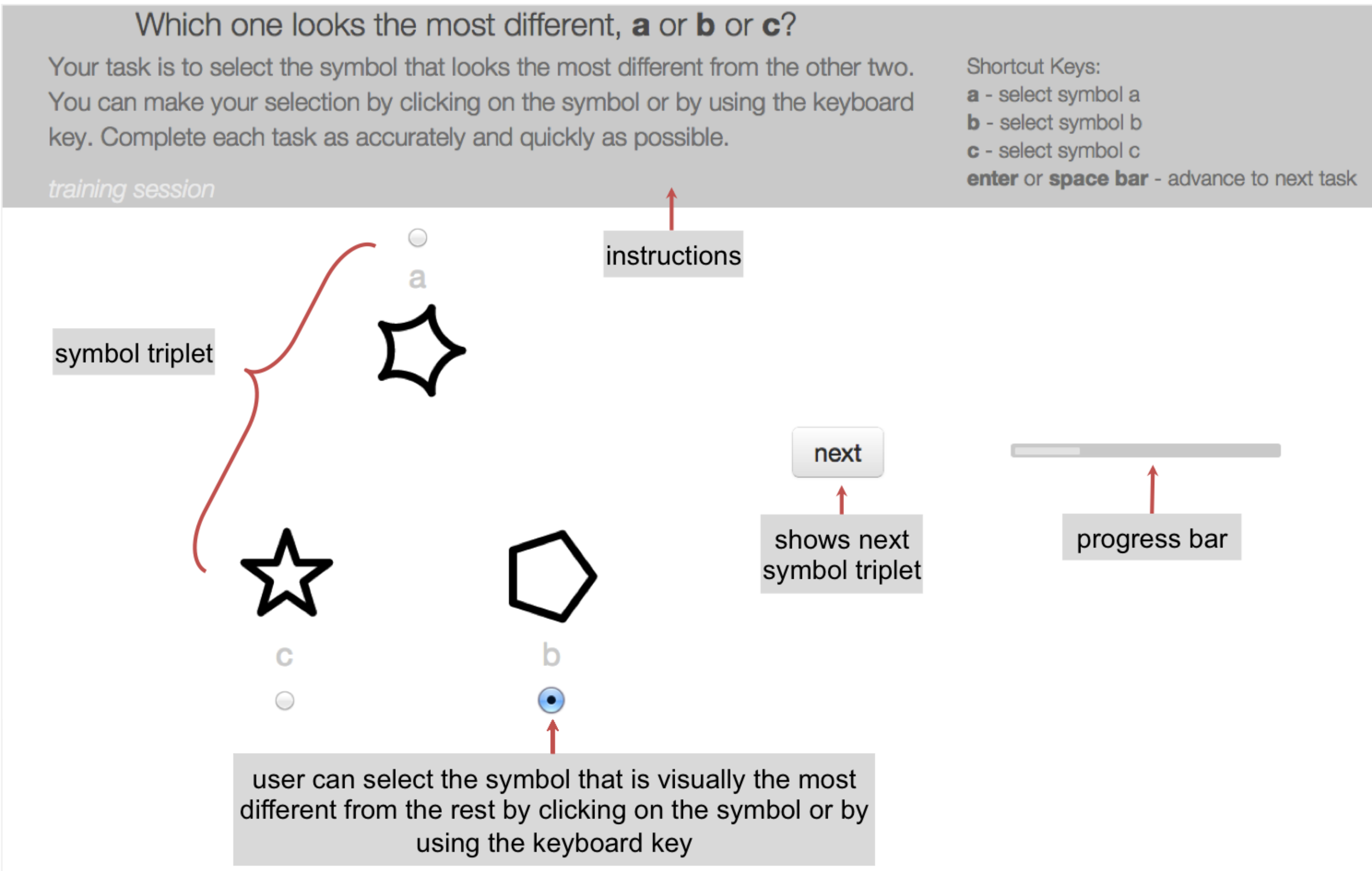
Judgment Tasks

3. Triplet ranking with matching (Tm)



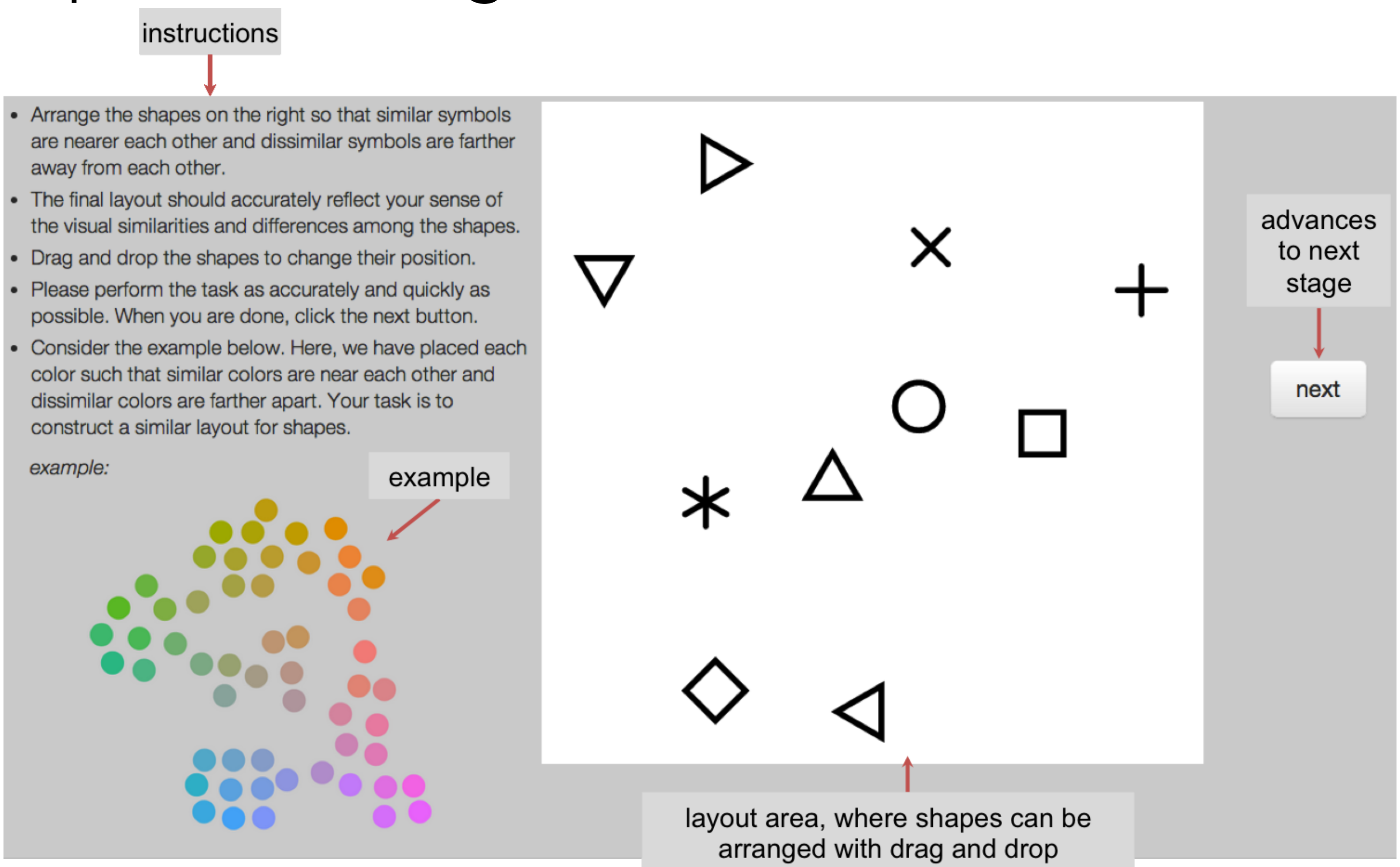
Judgment Tasks

4. Triplet ranking with discrimination (Td)



Judgment Tasks

5. Spatial arrangement (SA)



Judgment Tasks

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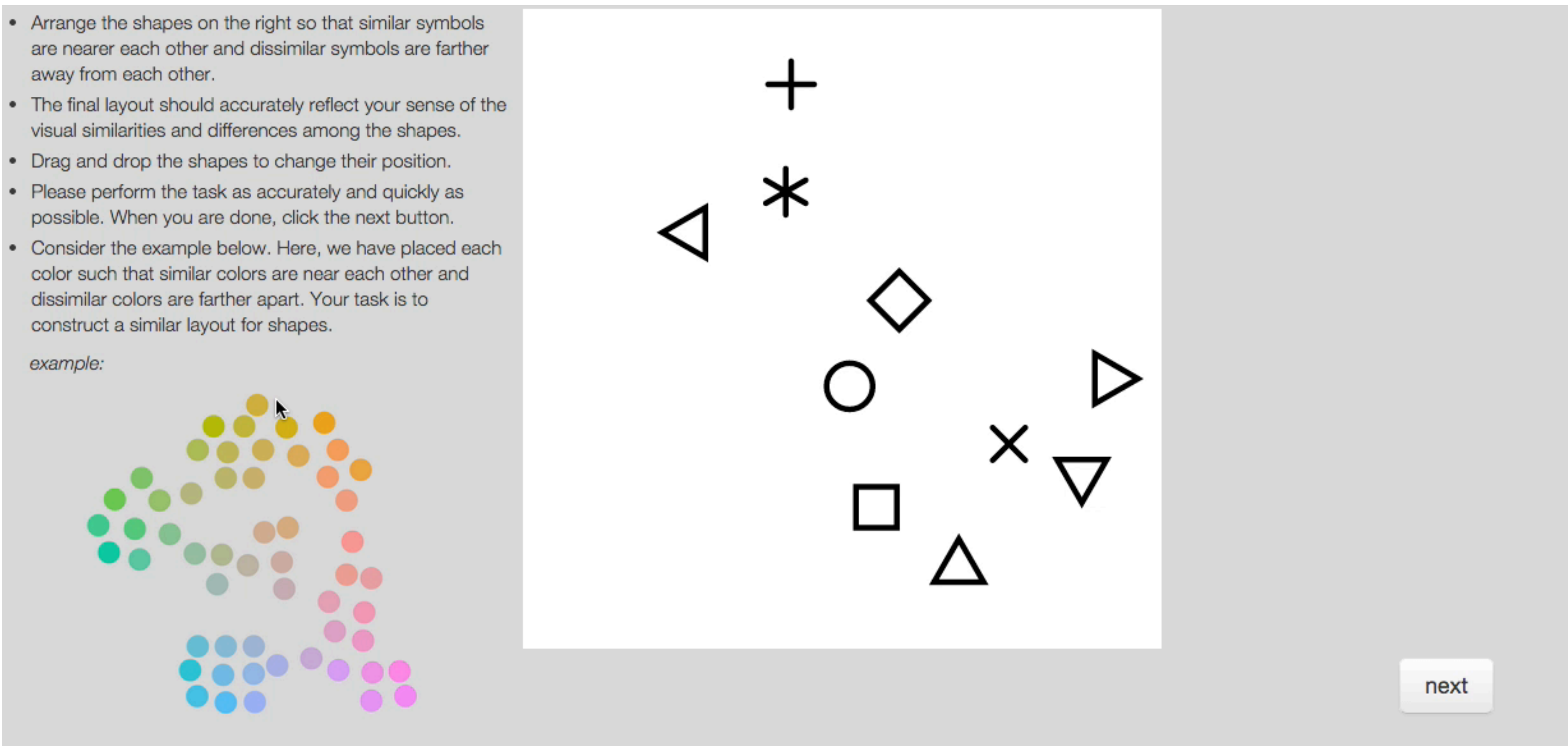
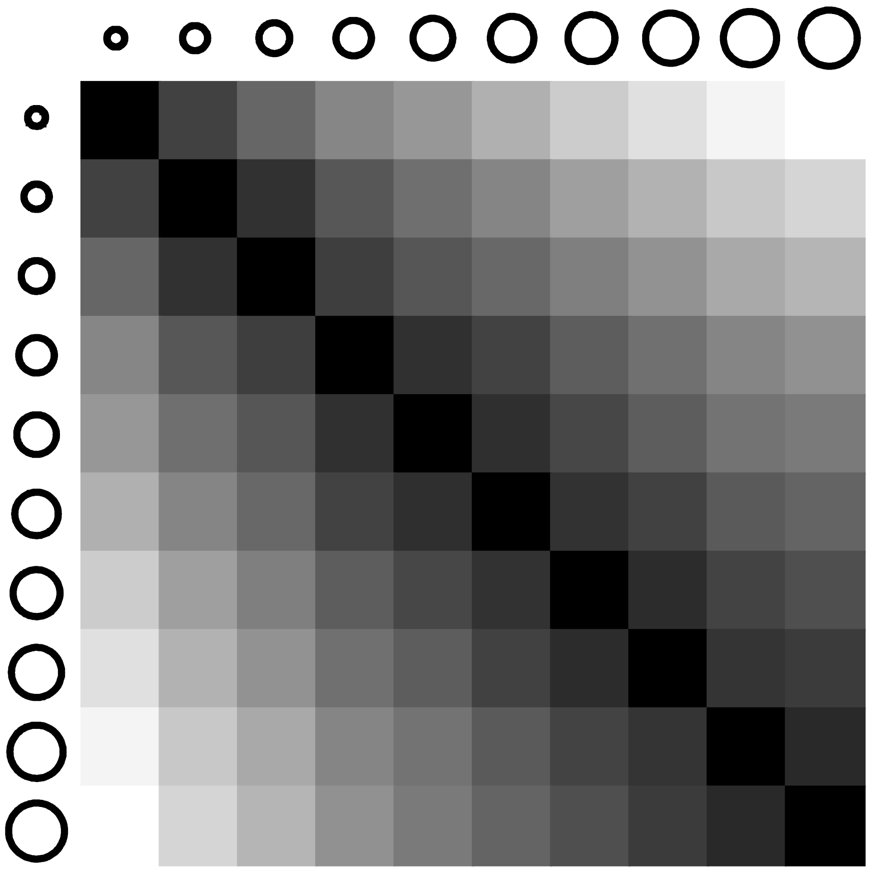
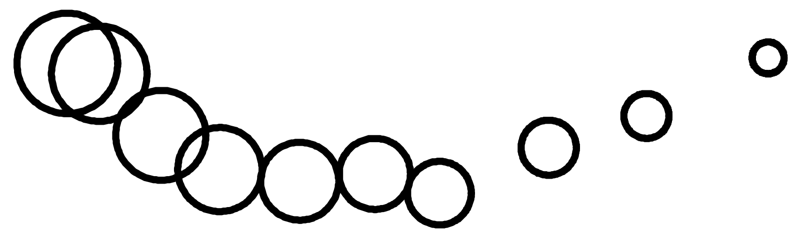


Perceptual Kernels & Models of Perception

Size (Tm)



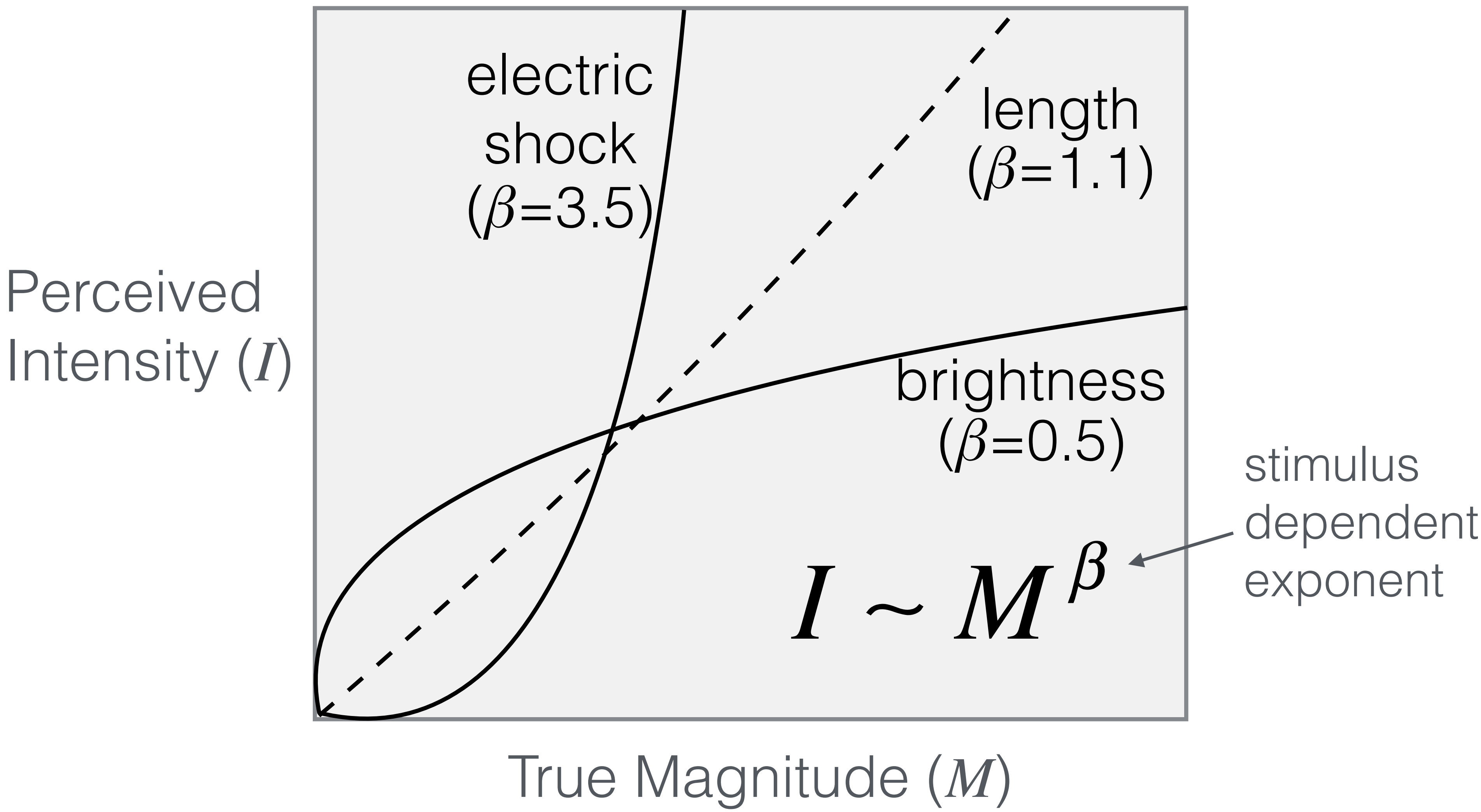
perceptual kernel



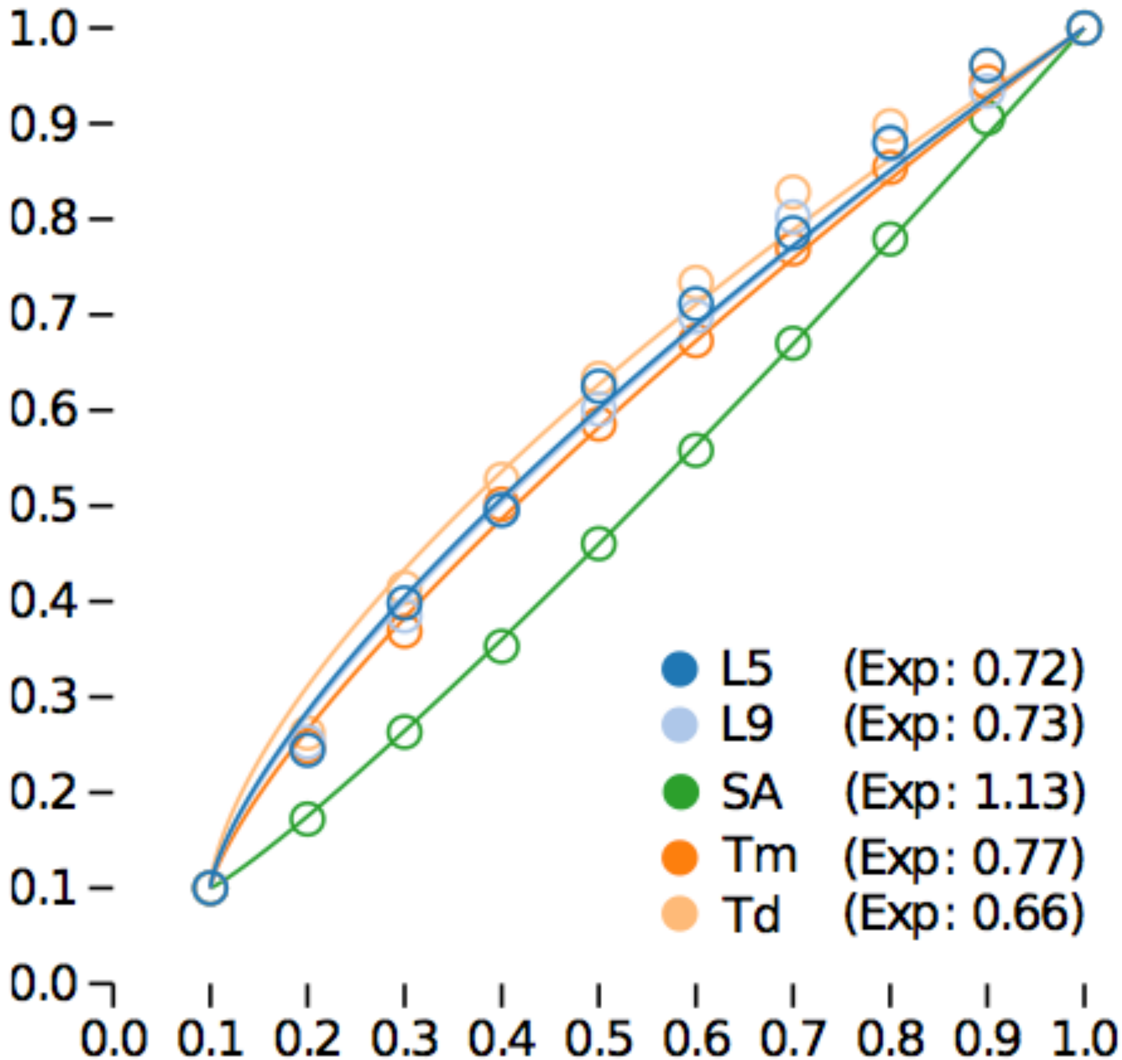
2D projection

Consistent with Stevens' Power Law!

Stevens' Power Law



Stevens' Power Law Fit



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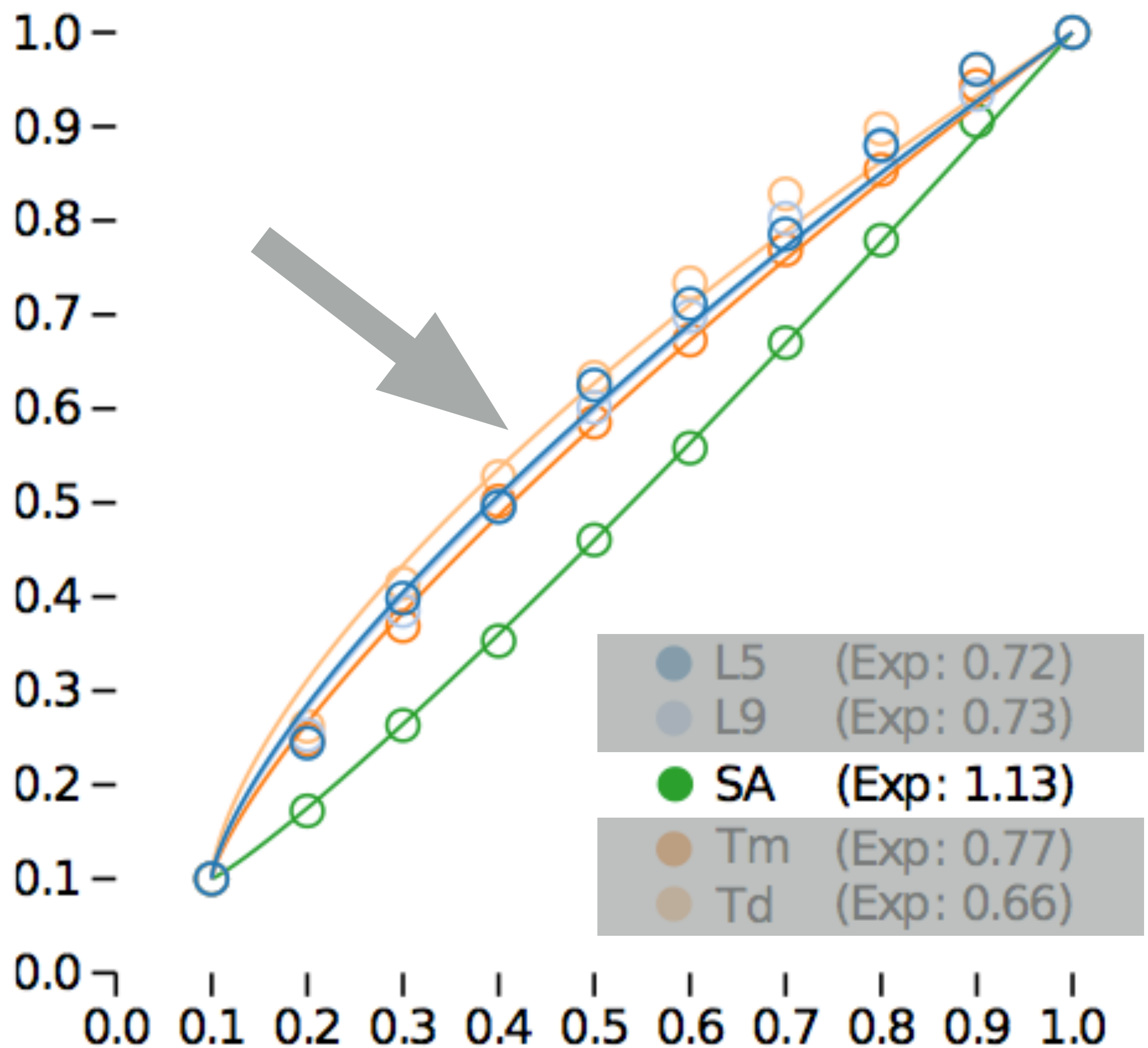
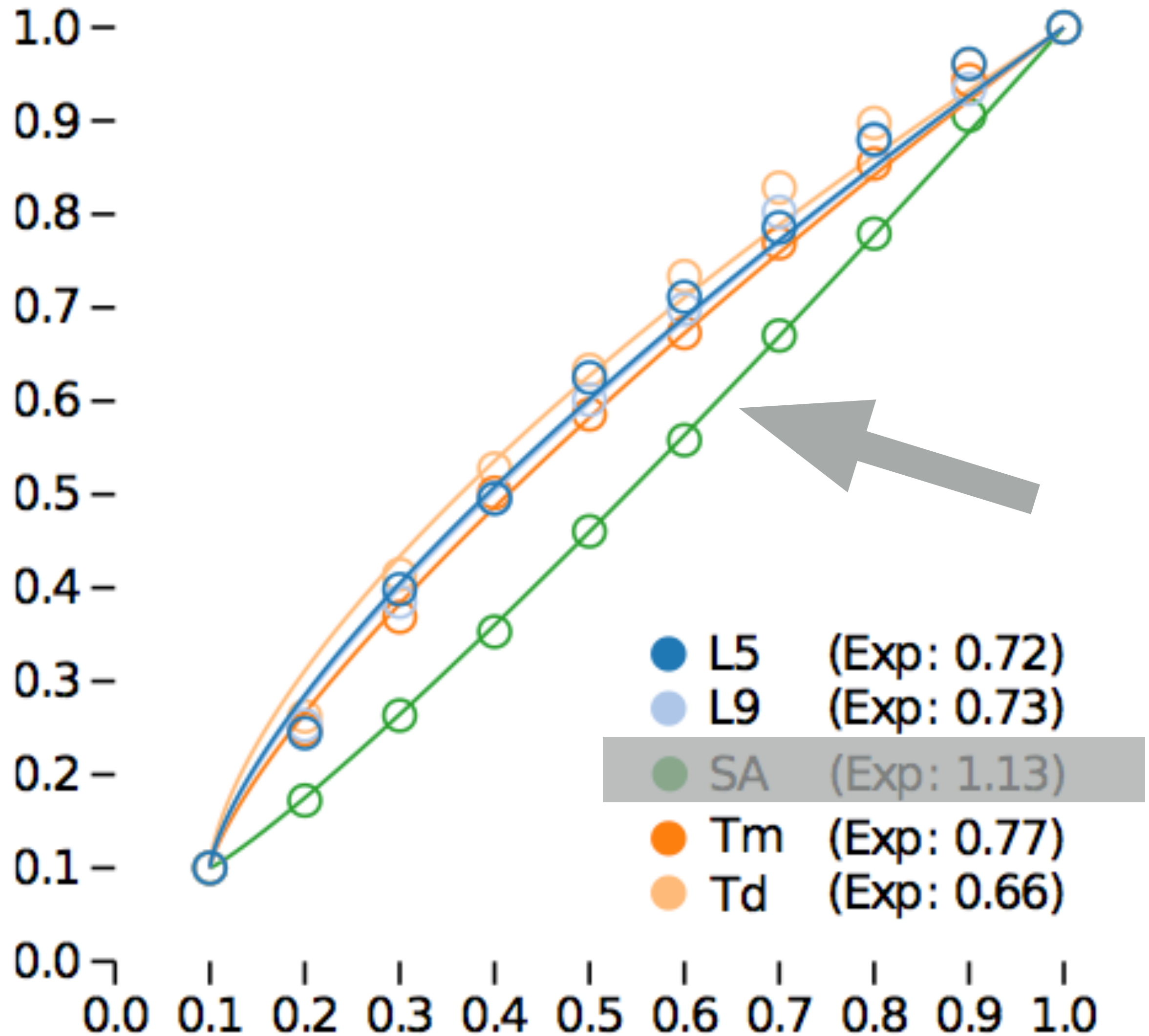
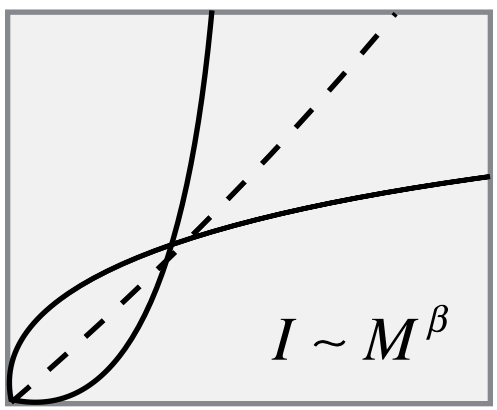


Stevens' Power Law Fit

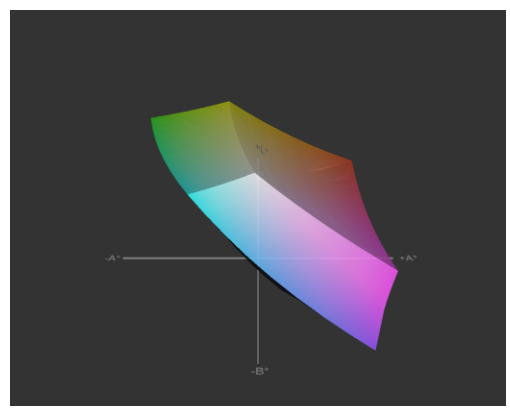


CONTRIBUTIONS

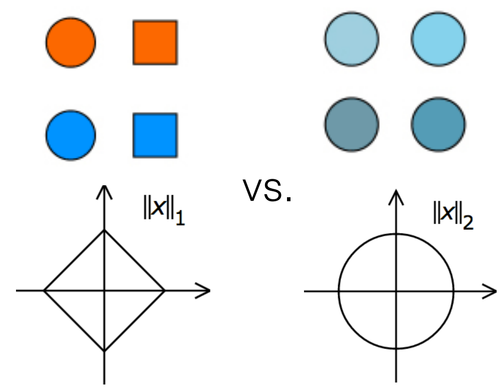
3) Assess using existing models



Stevens' Power Law



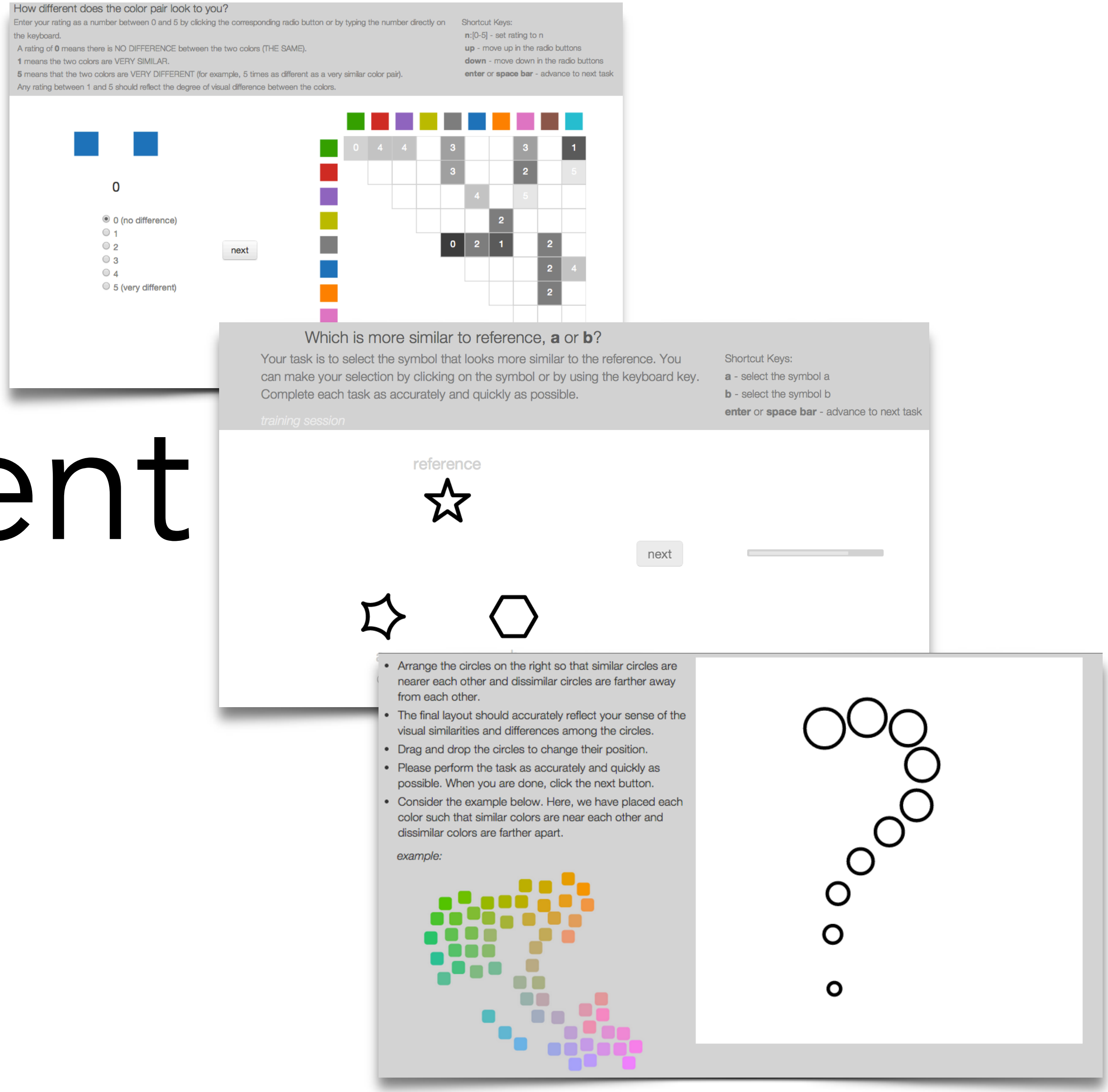
CIELAB
CIEDE2000
Color Names

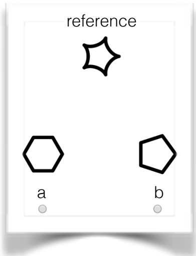


Garner's Integrality

details are in the paper

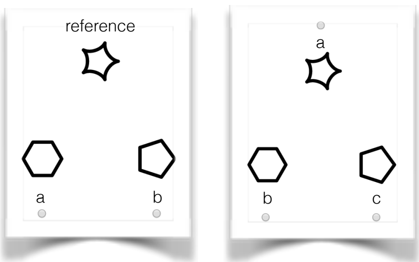
Which Judgment Task to Use?





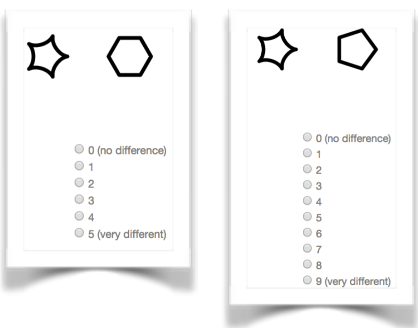
Triplet matching (Tm)

lowest variance, most robust, shortest unit



Triplet comparisons (Tm & Td)

longest experiment time, highest cost



Pairwise Likert ratings (L5 & L9)

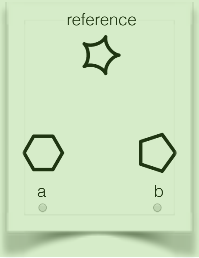
faster & cheaper than triplet comparisons

Manual spatial arrangement (SA)

fastest, cheapest

high variance, high sensitivity

best



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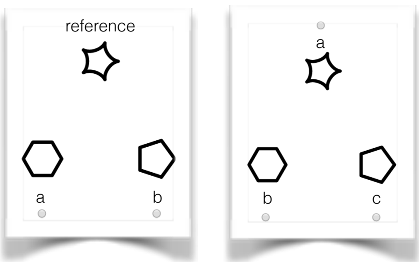

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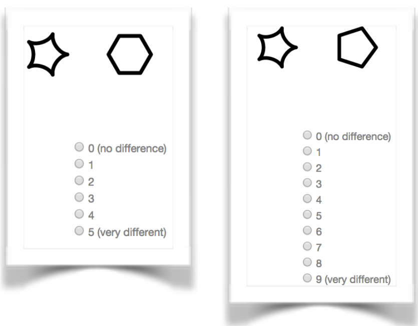

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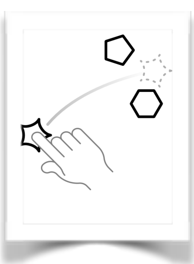

Manual spatial arrangement (SA)

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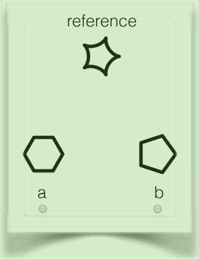
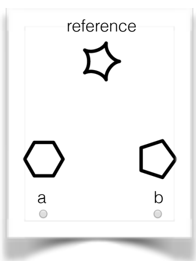
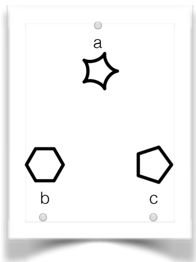


Triplet matching (Tm)

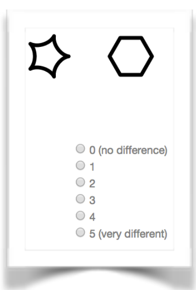
lowest variance, most robust, shortest unit





Triplet comparisons (Tm & Td)

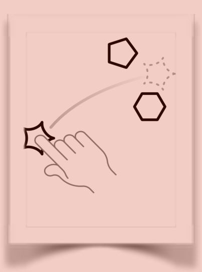
longest experiment time, highest cost



Pairwise Likert ratings (L5 & L9)

faster & cheaper than triplet comparisons

worst



Manual spatial arrangement (SA)

fastest, cheapest

high variance, high sensitivity

CONCLUSIONS

Perceptual Kernels

operational model

Use ordinal triplet matching

unless prohibited by time & cost

Avoid manual spatial arrangement

Read the paper

Acknowledgments

IDL Group Members

ISTC BIG DATA

NSF

data & source code

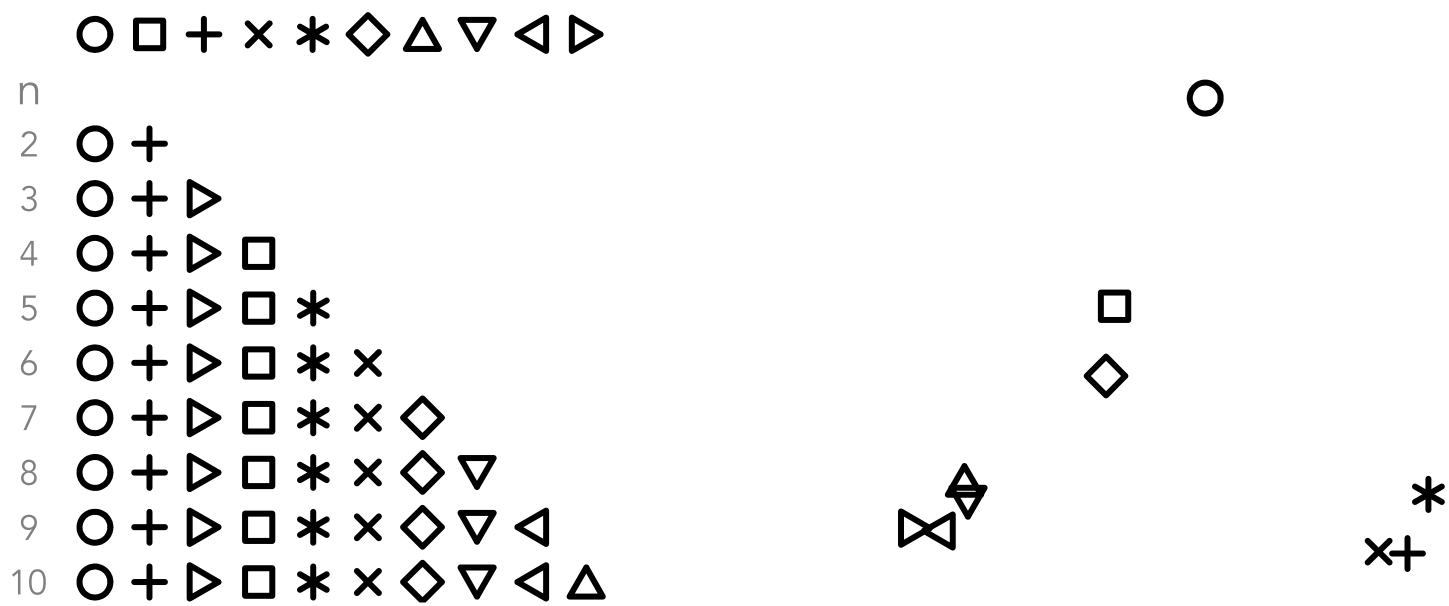
https://github.com/uwdata/perceptual-kernels

https://github.com/uwdata/visual-embedding

Data Processing

- Pairwise judgments
  - Produce a distance matrix directly
  - Identical pairs to detect spammers
- Triplet judgments
  - Generalized non-metric multidimensional scaling
  - Use triplets with two identical elements to detect spammers
- Spatial arrangements
  - Align to a reference and filter-out the outliers
  - Planar Euclidean distances produce a distance matrix

Palette Design

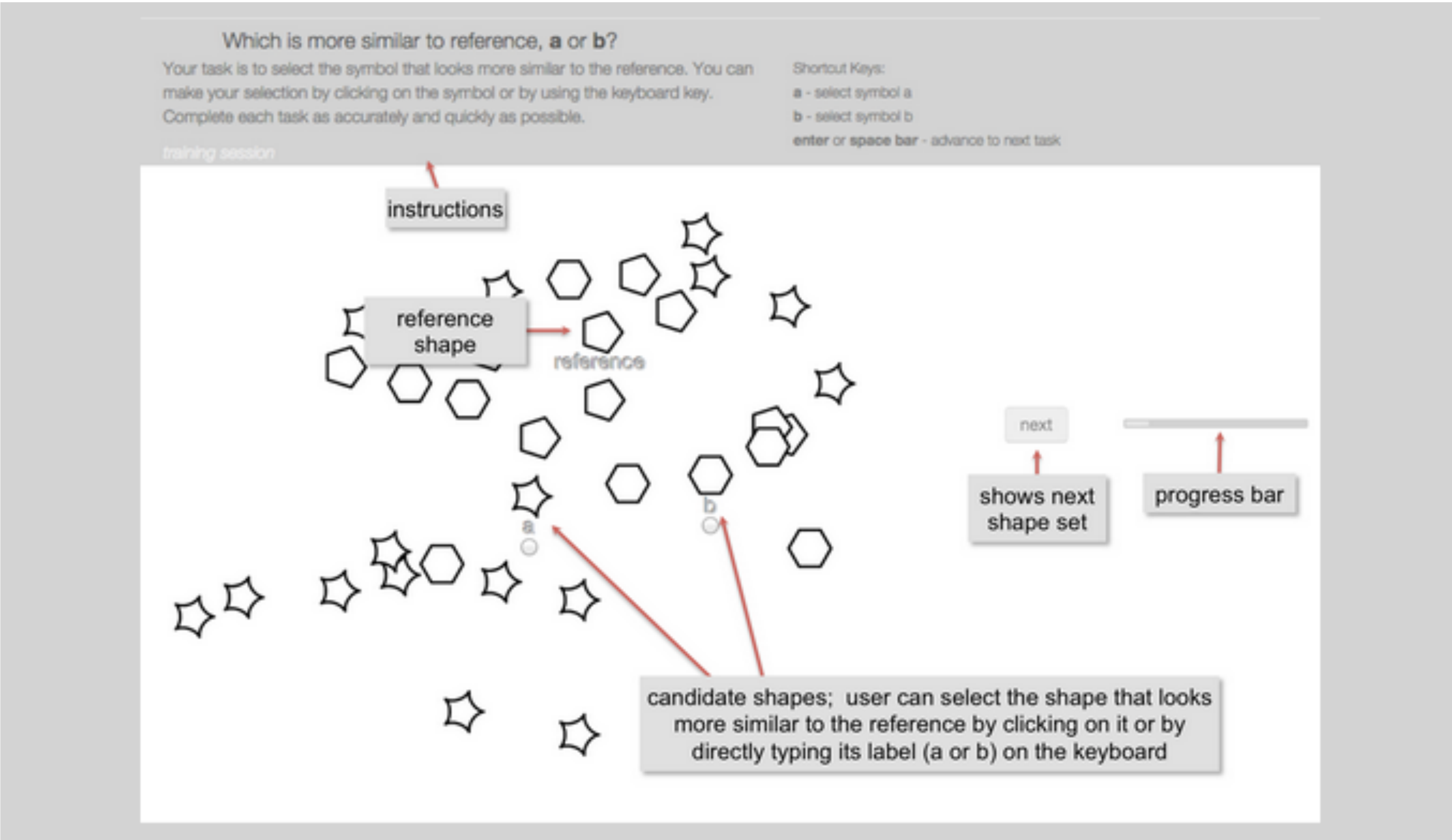


What About Context?

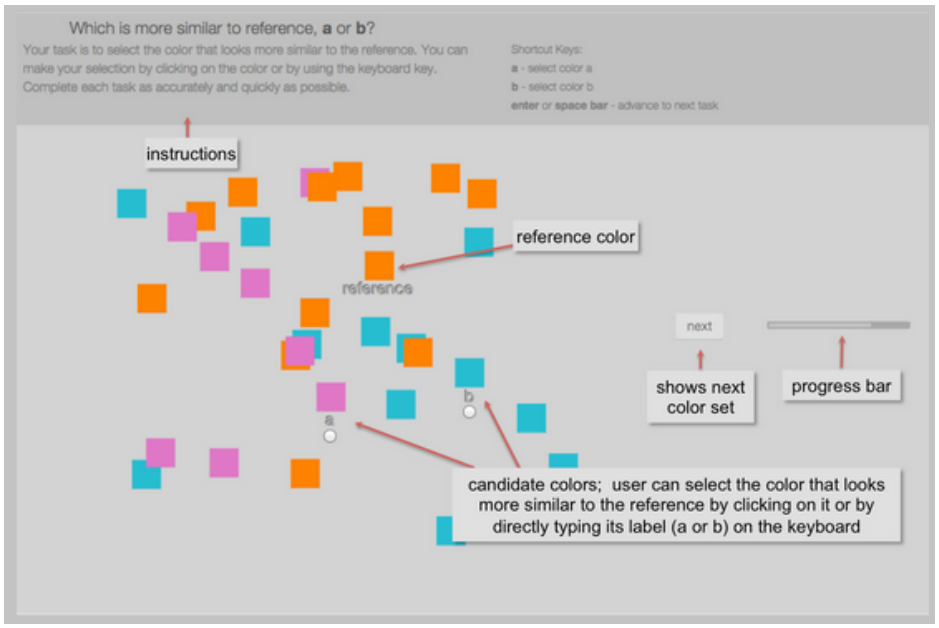
What About Context?

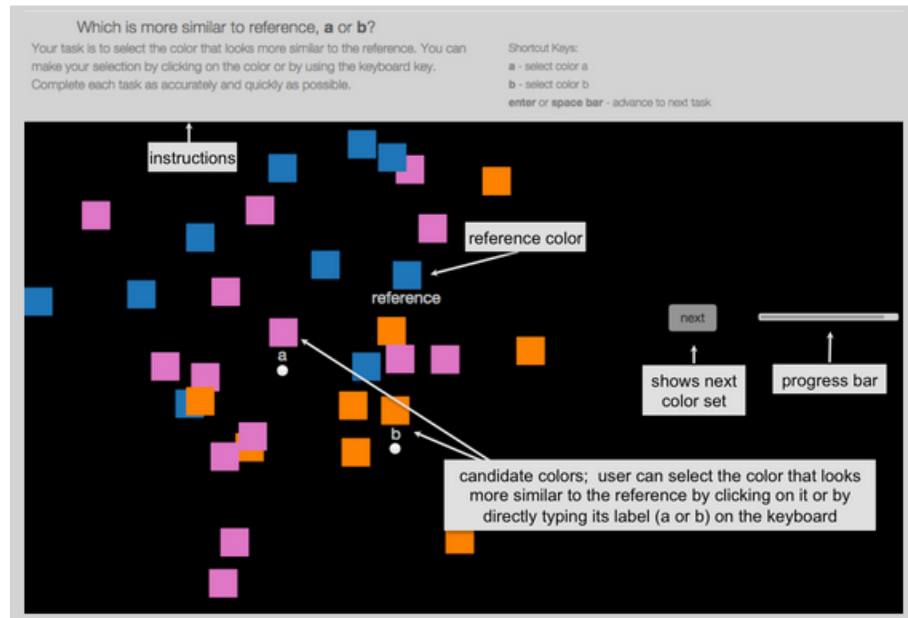
What about it?

What About Context?



What About Context?





early results suggest no significant effect

Why Tableau?

Why Tableau?

I have Tableau stocks

Why Tableau?

I have Tableau stocks?

Why Tableau?

~~I have Tableau stocks?~~

Why Tableau?

Manually designed with perceptual considerations in mind

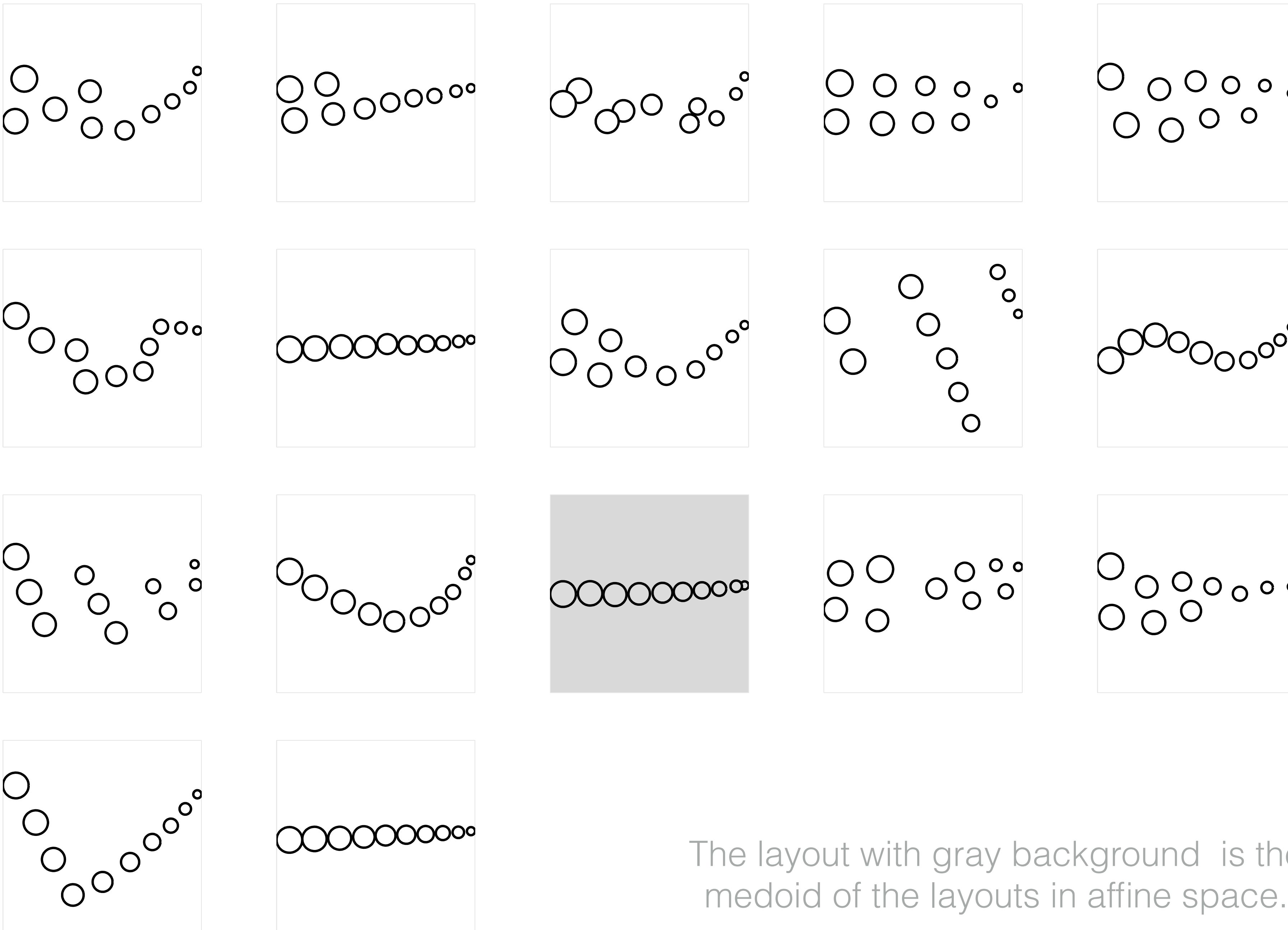
discriminability, saliency and naming of colors, robustness to spatial overlap of shapes

Provides

ecological validity and good baseline

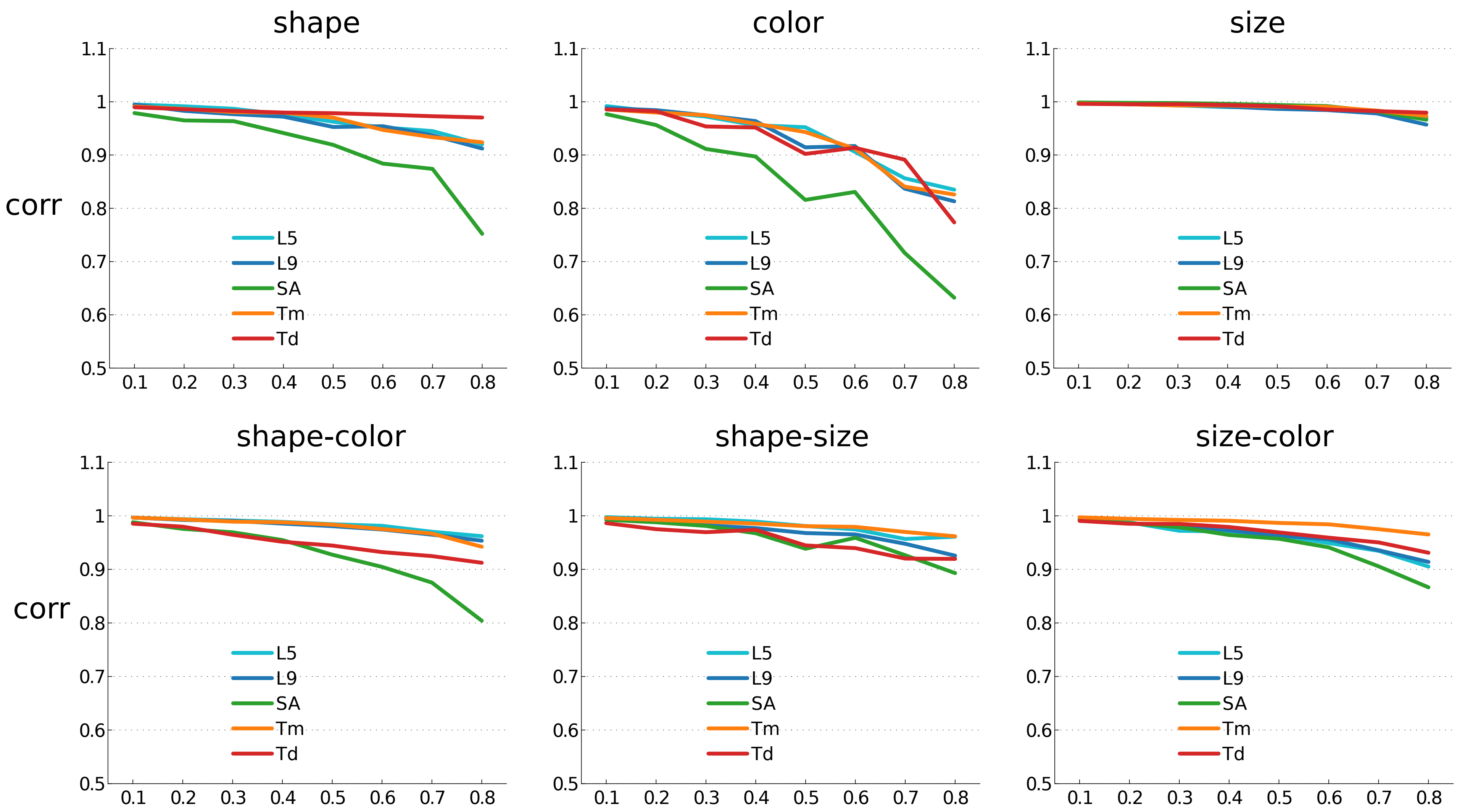
What About Individual Differences?

Per-subject SAs: size



The layout with gray background is the medoid of the layouts in affine space.

Sensitivity



Why SA Performs Poorly?

Why SA Performs Poorly?

Unstructured nature, leading to higher variance across subjects

Expressivity limited to two dimensions expression of perceptual structures.

Why Tm Outperforms Td?

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It involves a binary decision (vs. trinary)

Detects more fine-grained similarities

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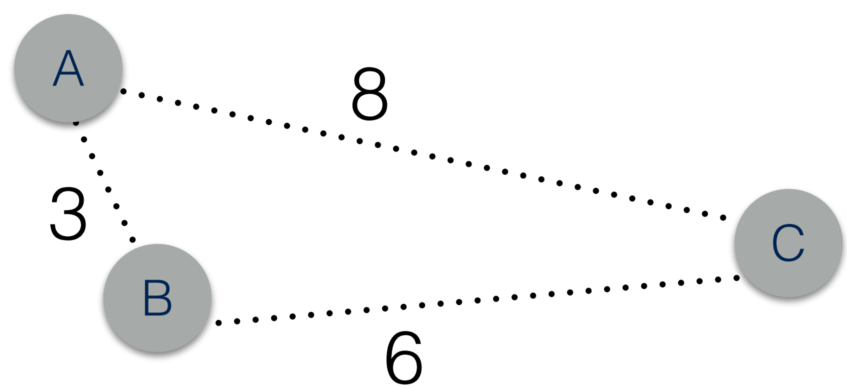

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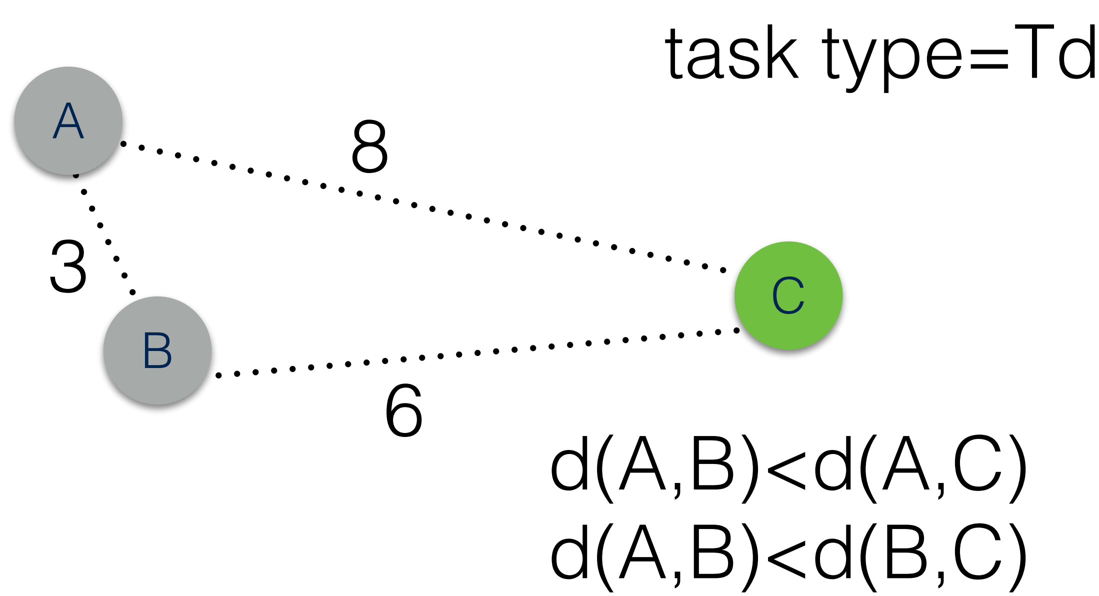

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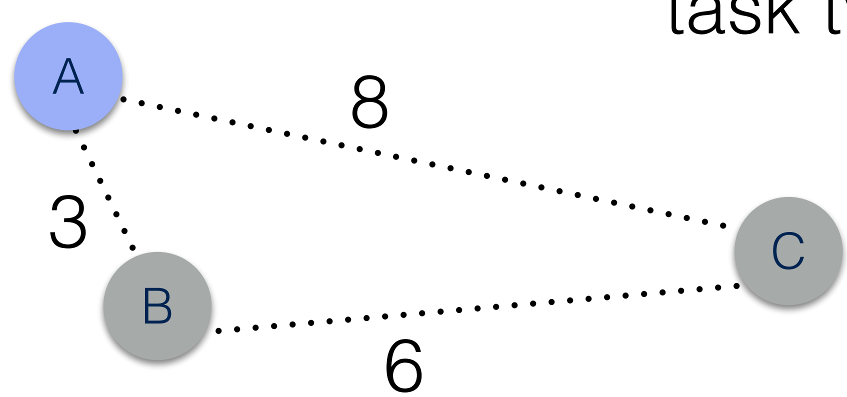

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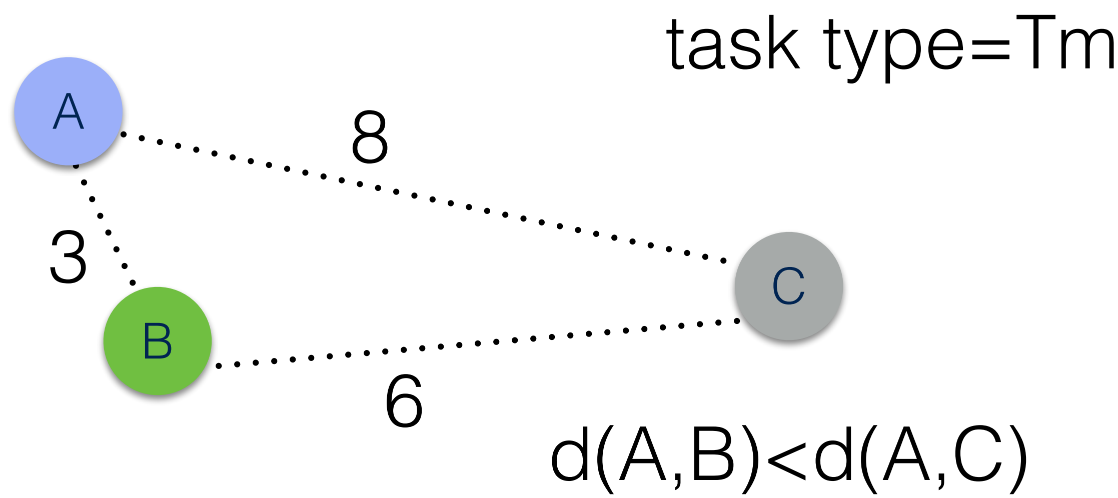

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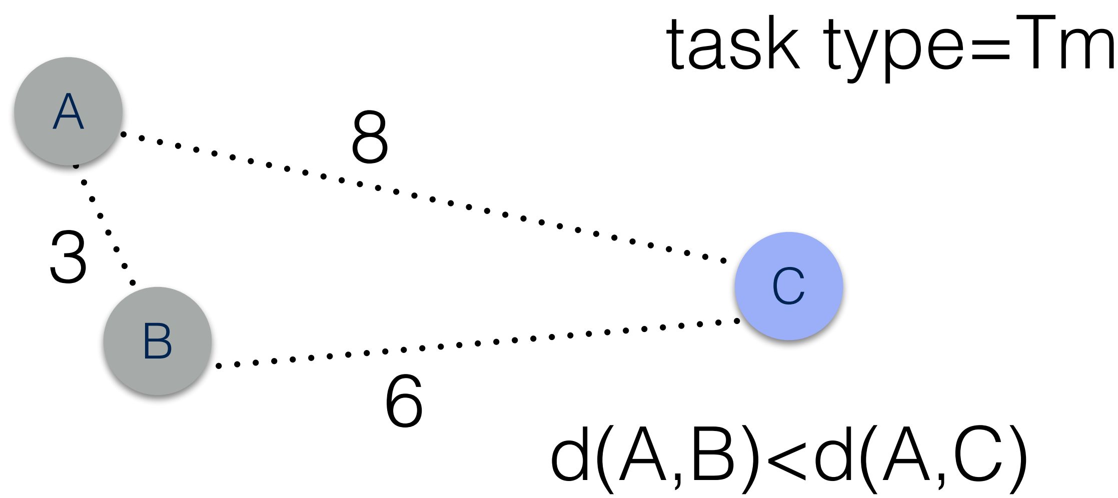

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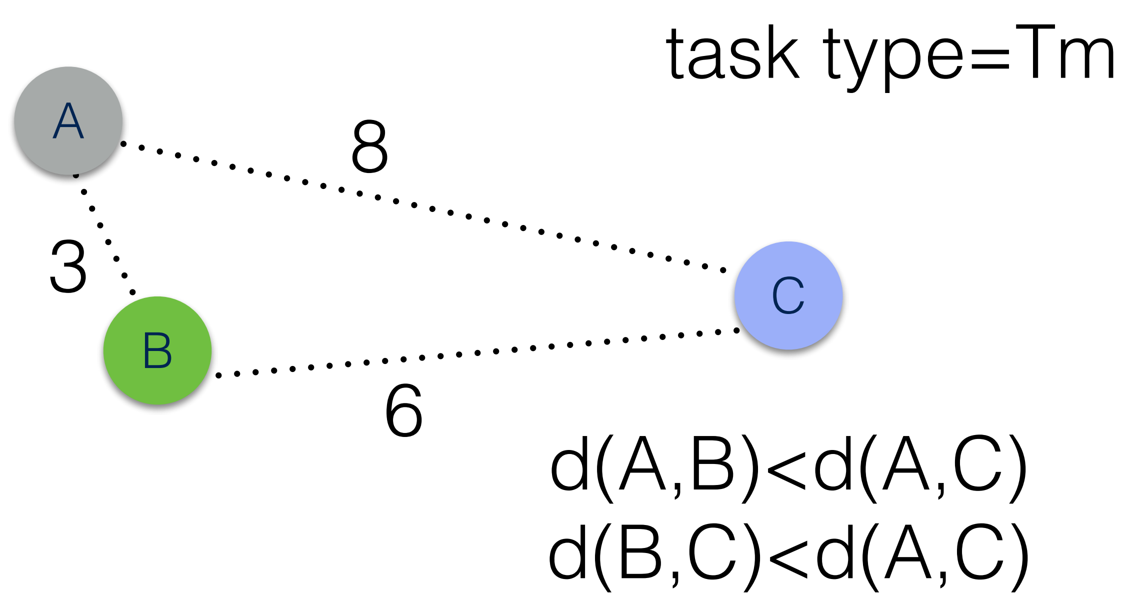
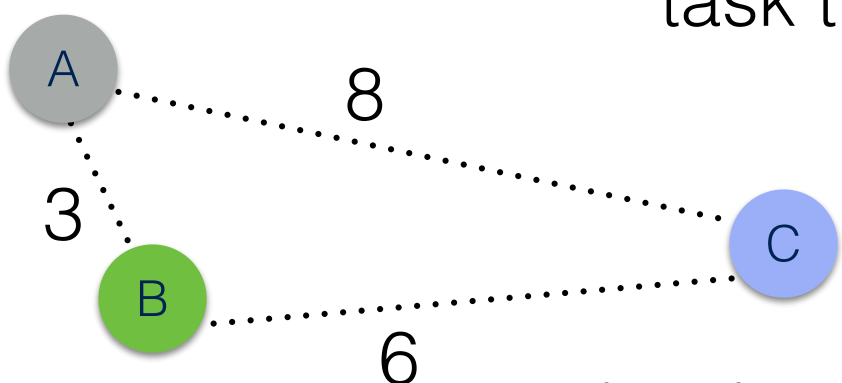


Why Tm Outperforms Td?

It involves a binary decision (vs. trinary)

Detects more fine-grained similarities

task type=Tm

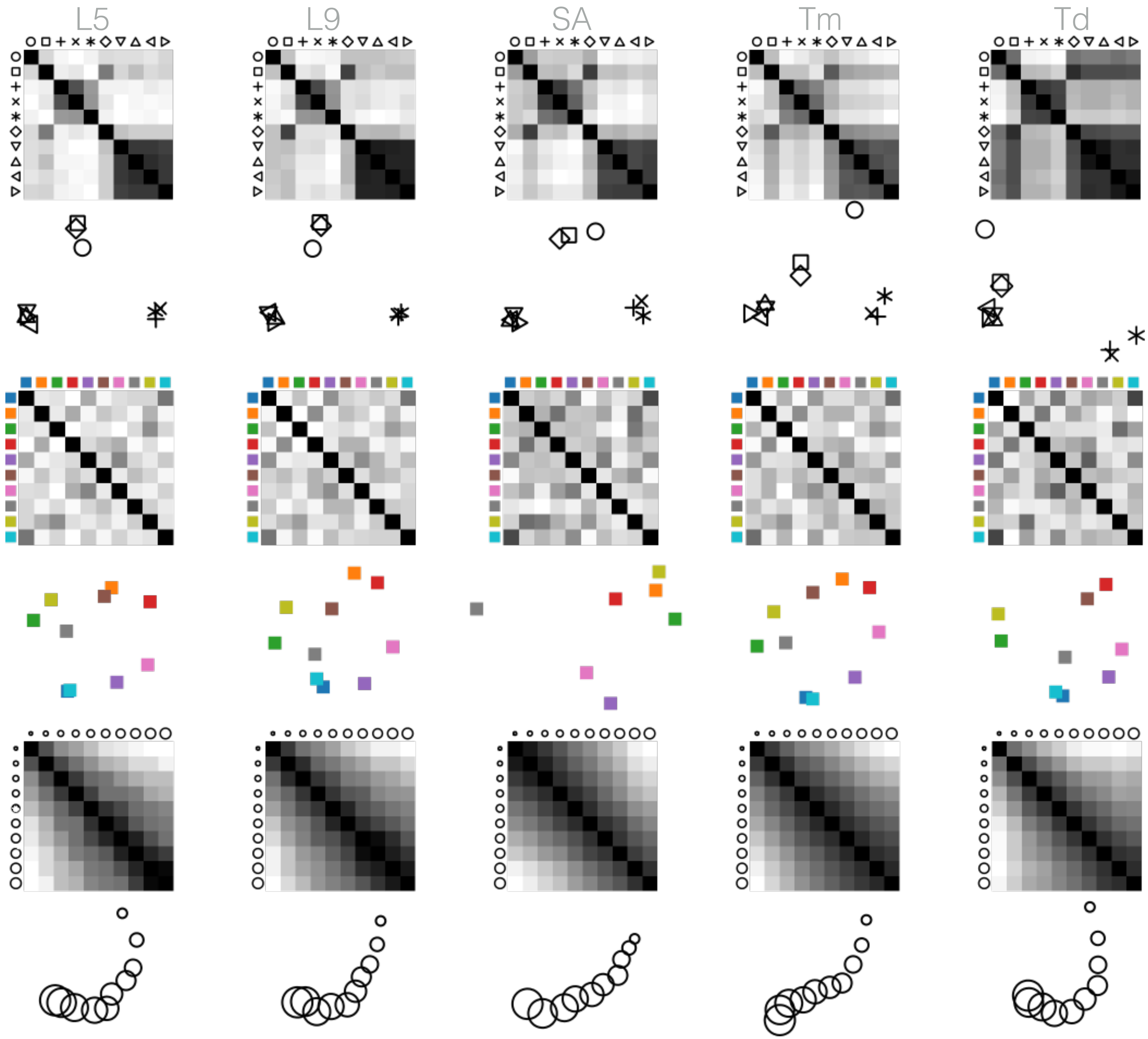


d(A,B)<d(A,C)

d(B,C)<d(A,C)

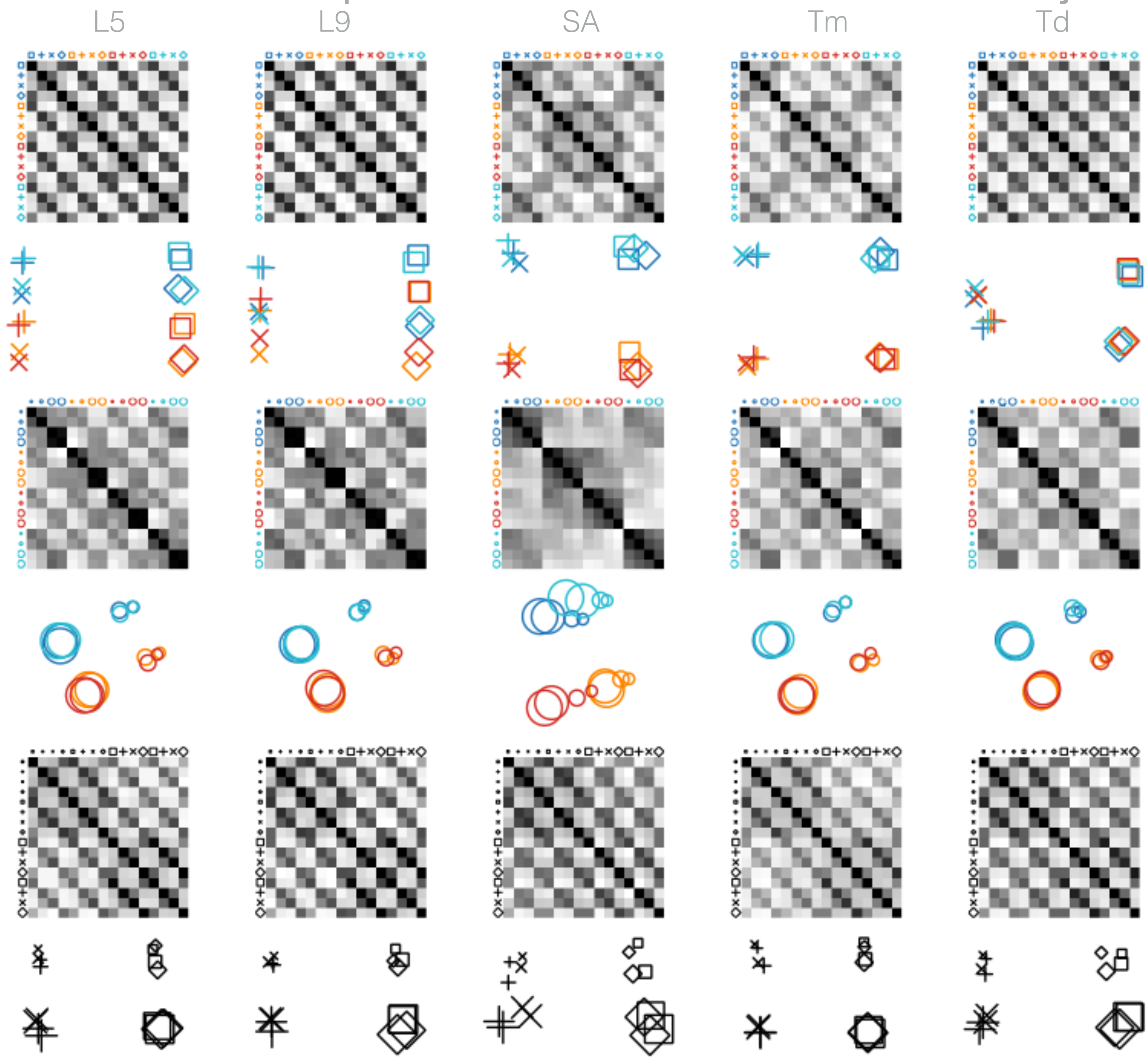
Td cannot elicit

Univariate Perceptual Kernels with MDS Projections*

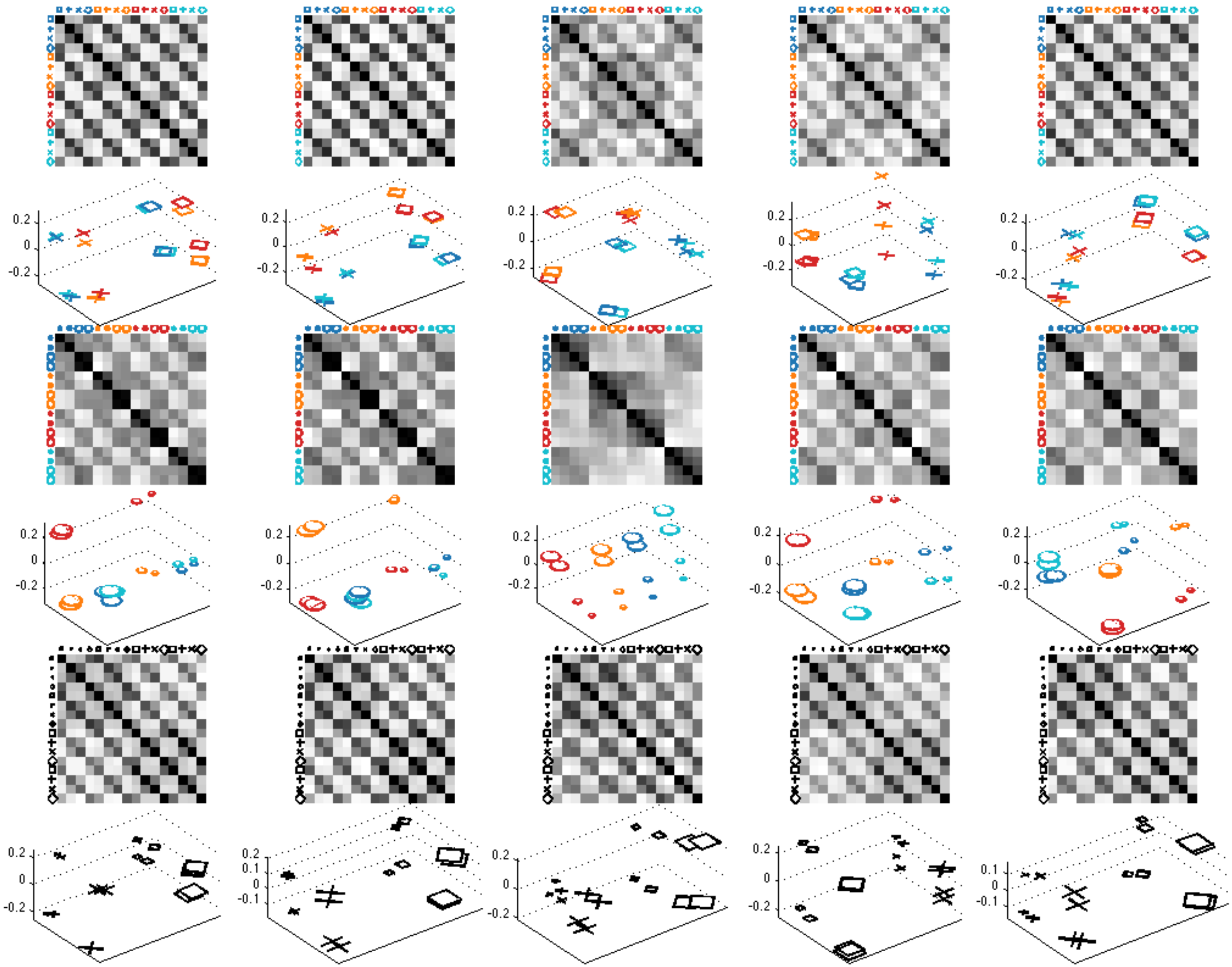


*For each visual variable, projections are aligned to the projection of the L5 kernel

Bivariate Perceptual Kernels with MDS Projections



Bivariate Perceptual Kernels with 3D MDS Projections



Comparison of Perceptual Kernels with Color Models: Rank Correlation Matrices

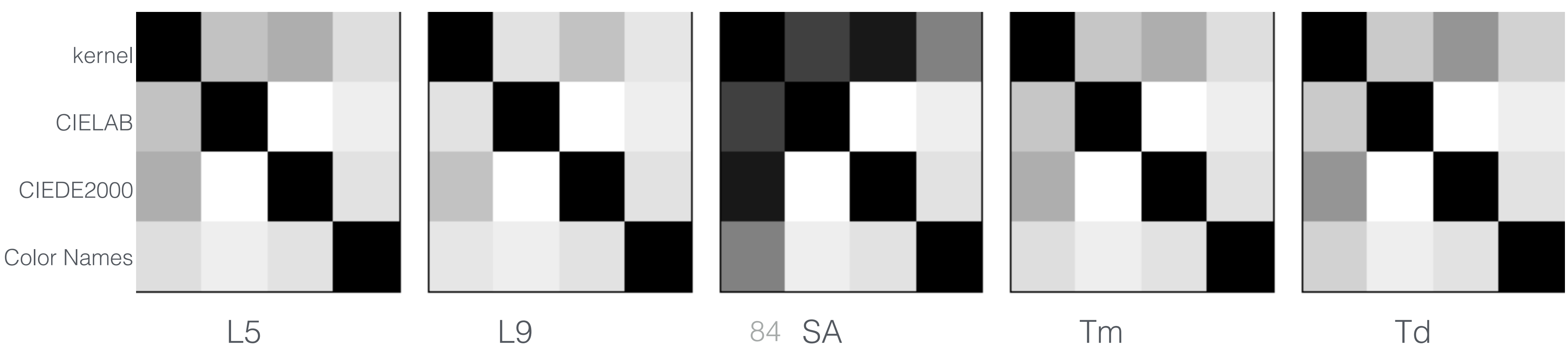
	kernel (L5)	CIELAB	CIEDE2000	Color Names
kernel (L5)	1.00	0.67	0.59	0.76
CIELAB	0.67	1.00	0.88	0.82
CIEDE2000	0.59	0.88	1.00	0.77
Color Names	0.76	0.82	0.77	1.00

	kernel (L9)	CIELAB	CIEDE2000	Color Names
kernel (L9)	1.00	0.77	0.66	0.79
CIELAB	0.77	1.00	0.88	0.82
CIEDE2000	0.66	0.88	1.00	0.77
Color Names	0.79	0.82	0.77	1.00

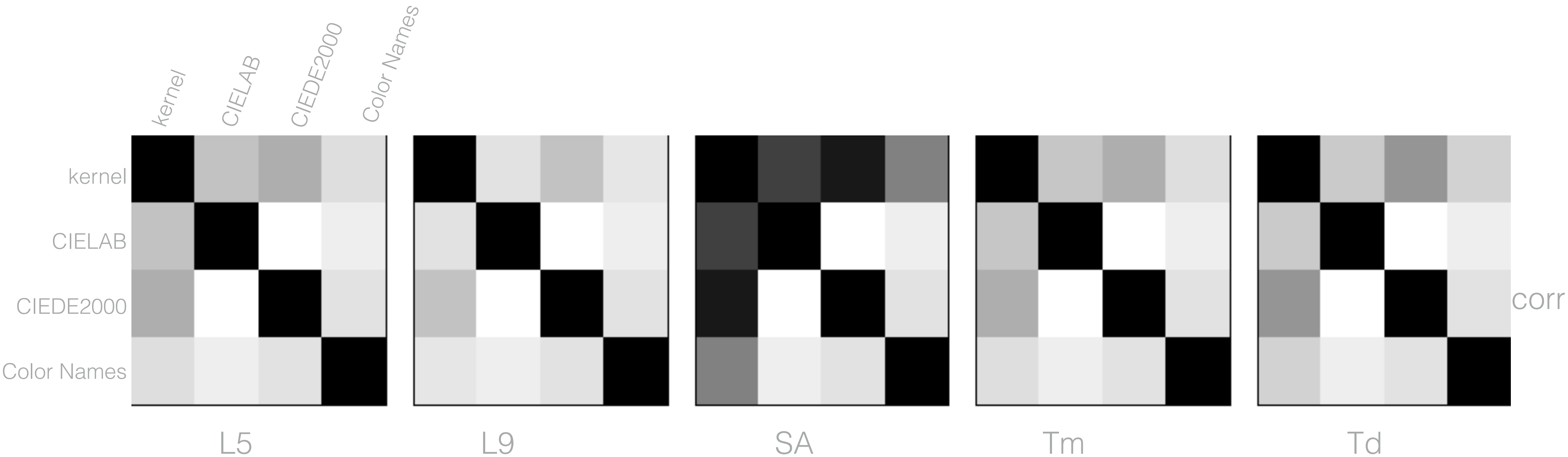
	kernel (SA)	CIELAB	CIEDE2000	Color Names
kernel (SA)	1.00	0.23	0.09	0.45
CIELAB	0.23	1.00	0.88	0.82
CIEDE2000	0.09	0.88	1.00	0.77
Color Names	0.45	0.82	0.77	1.00

	kernel (Tm)	CIELAB	CIEDE2000	Color Names
kernel (Tm)	1.00	0.68	0.60	0.76
CIELAB	0.68	1.00	0.88	0.82
CIEDE2000	0.60	0.88	1.00	0.77
Color Names	0.76	0.82	0.77	1.00

	kernel (Td)	CIELAB	CIEDE2000	Color Names
kernel (Td)	1.00	0.69	0.51	0.72
CIELAB	0.69	1.00	0.88	0.82
CIEDE2000	0.51	0.88	1.00	0.77
Color Names	0.72	0.82	0.77	1.00

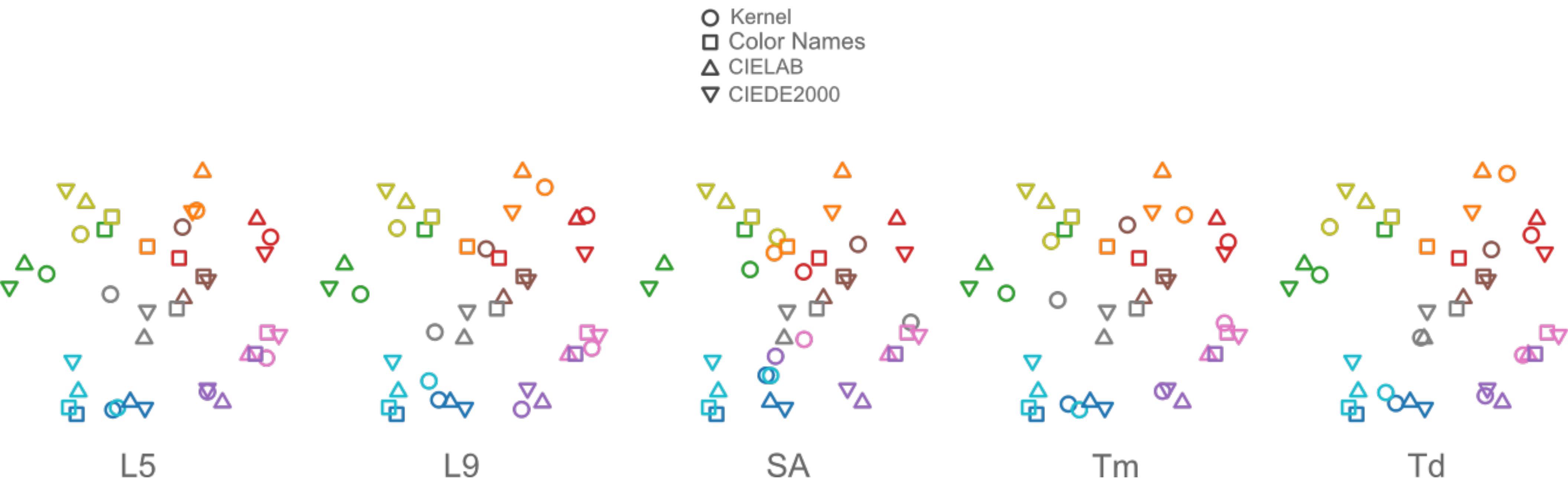


Comparison of Perceptual Kernels with Color Models



Rank correlation matrices displayed as gray-scale images (brighter entries indicate higher correlations)

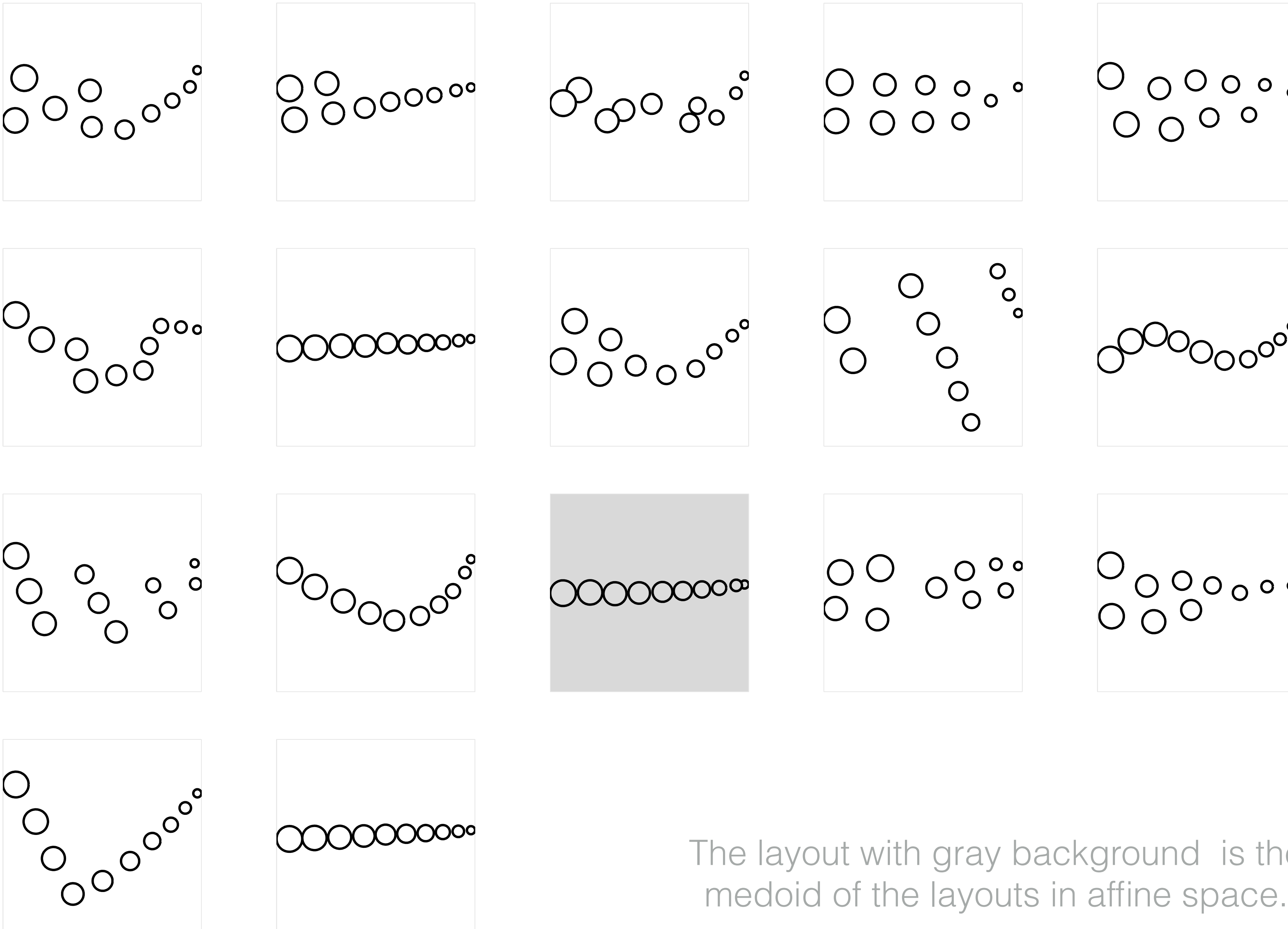
Comparison of Perceptual Color Kernels with Color Models



The palette shapes representing the models are chosen automatically with visual embedding (using the triplet matching kernel). They reflect the correlations between the variables. For example the correlation between the CIELAB and CIEDE2000 is higher than the correlation between the perceptual kernels and color names and the assigned shapes reflect this relationship perceptually.

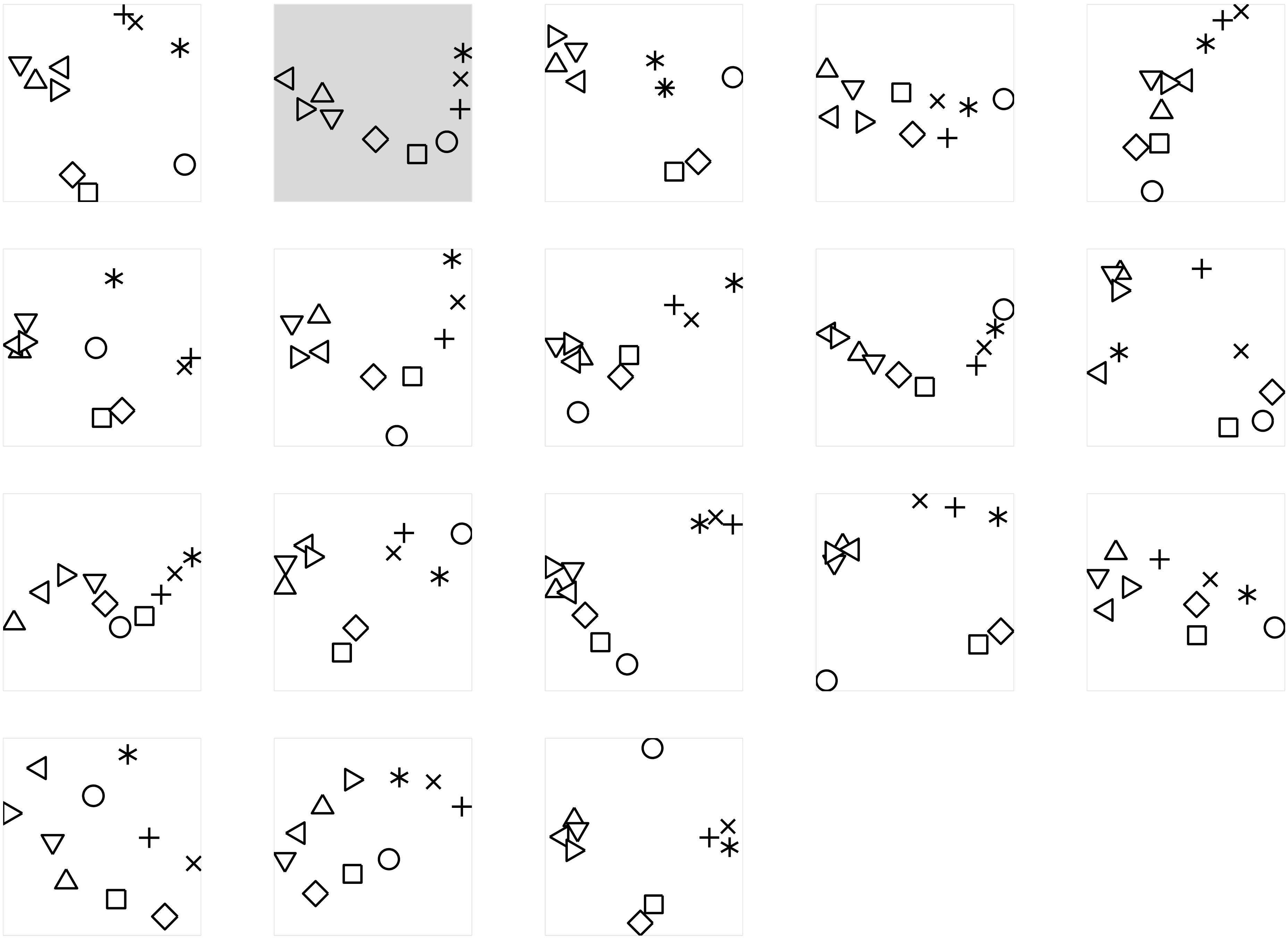
All projections are aligned to the CIELAB projection in the plane using similarity transformations

Per-subject SAs: size

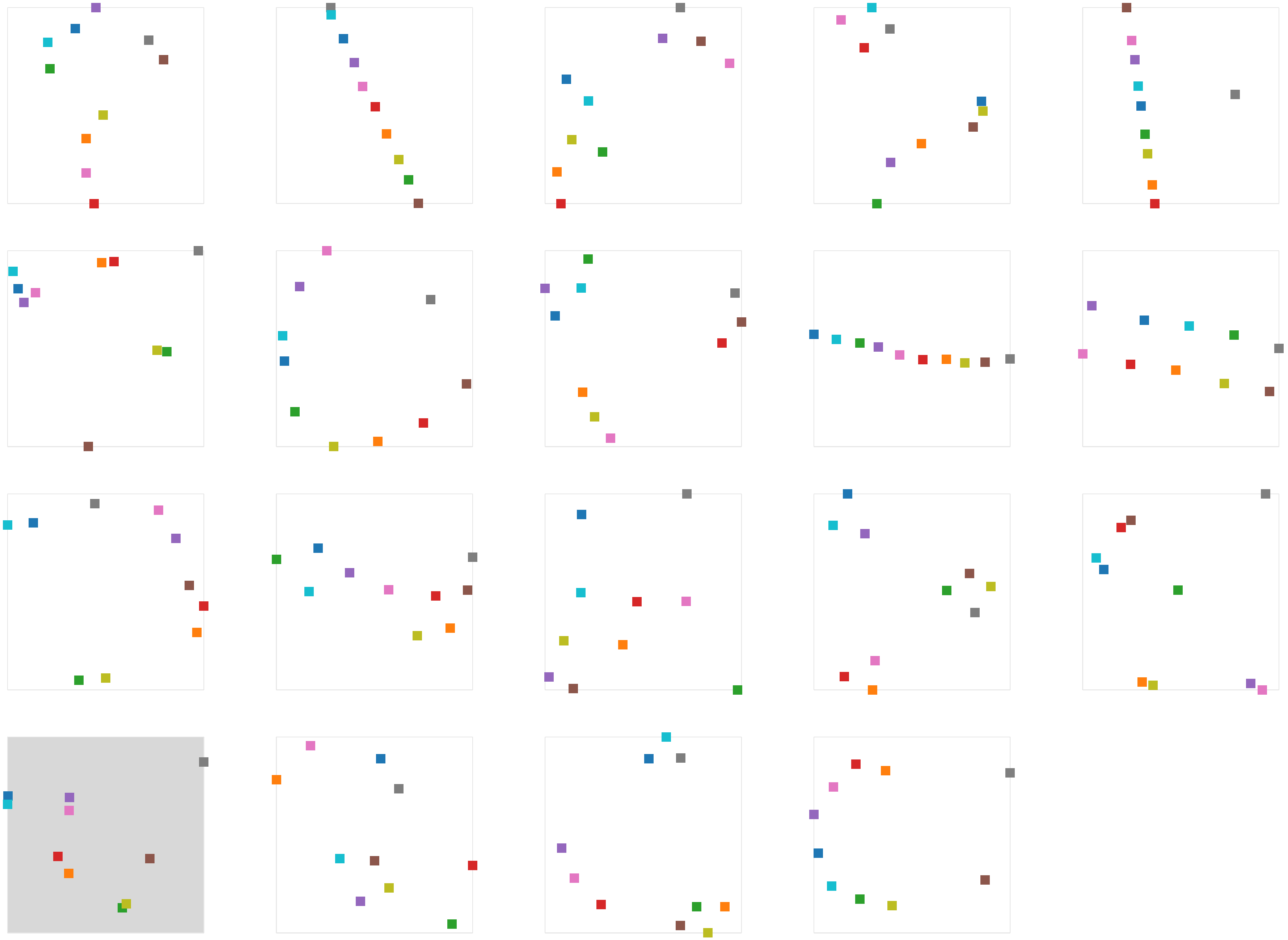


The layout with gray background is the medoid of the layouts in affine space.

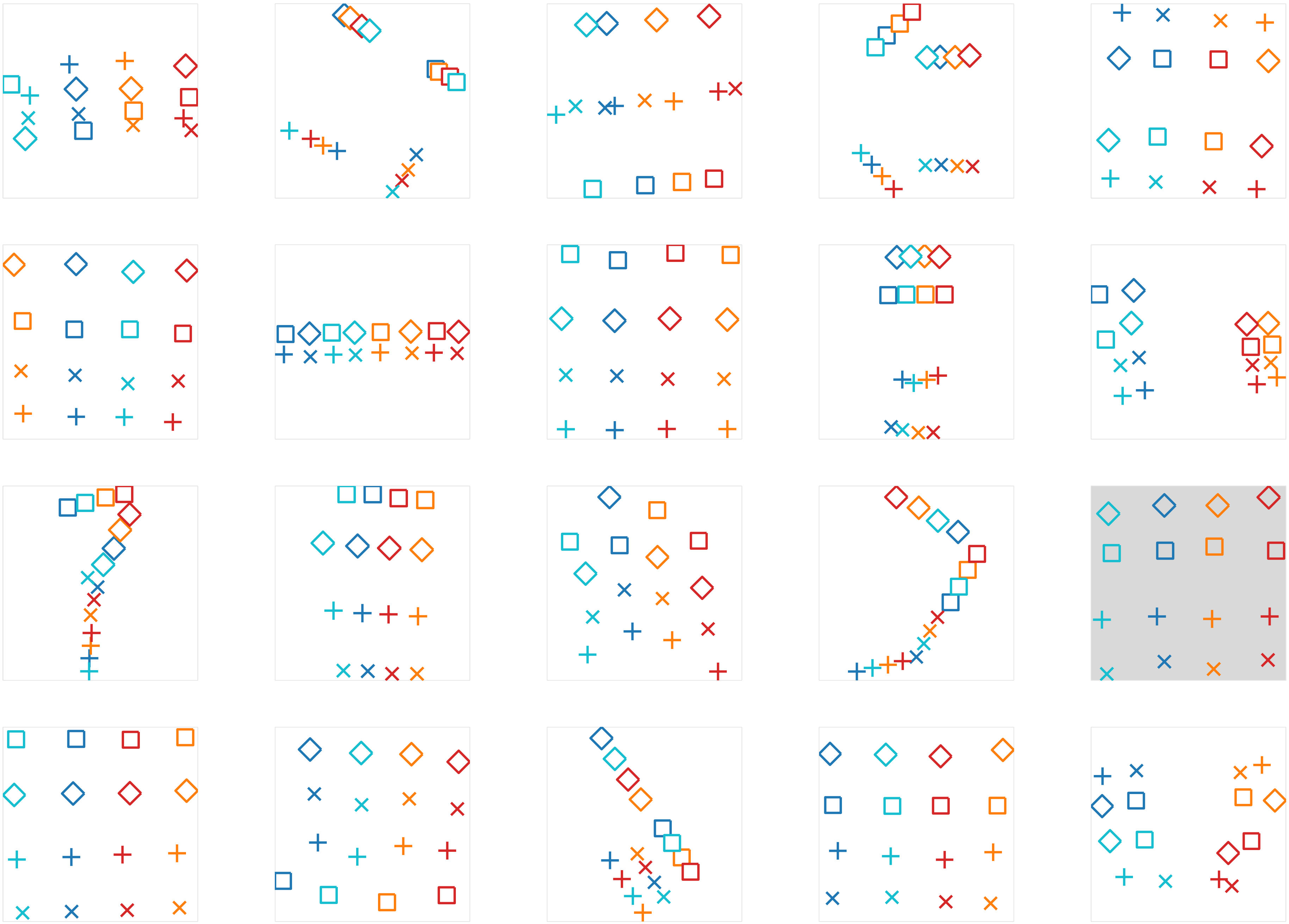
Per-subject SAs: shape



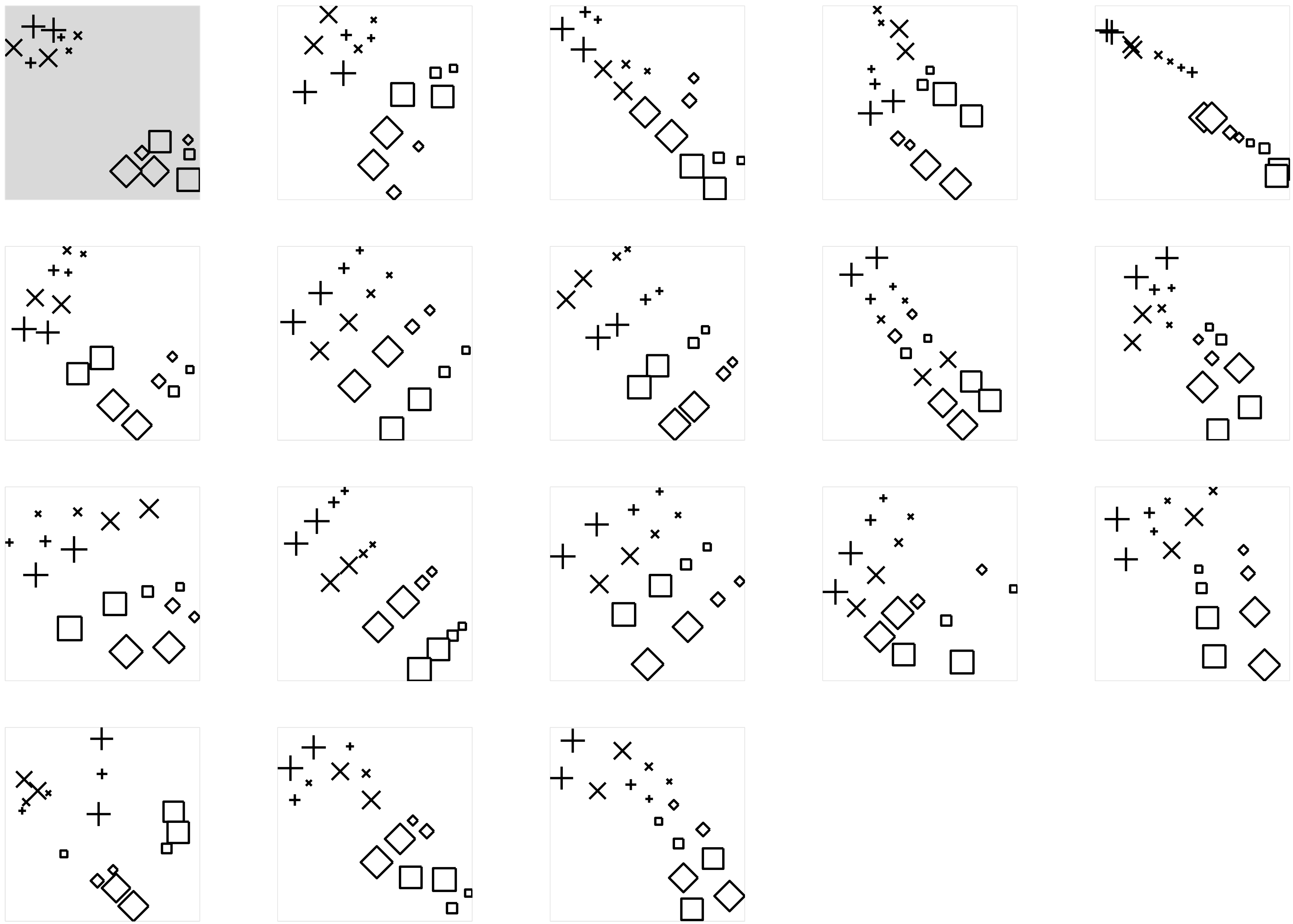
Per-subject SAs: color



Per-subject SAs: shape-color



Per-subject SAs: shape-size



Per-subject SAs: size-color