Storytelling with data

05 | visual design, data encodings, perceptual psychology

Scott Spencer | Columbia University

main course deliverables

Why show data graphically?

 graphic of a datum — effective? Conveys meaning?

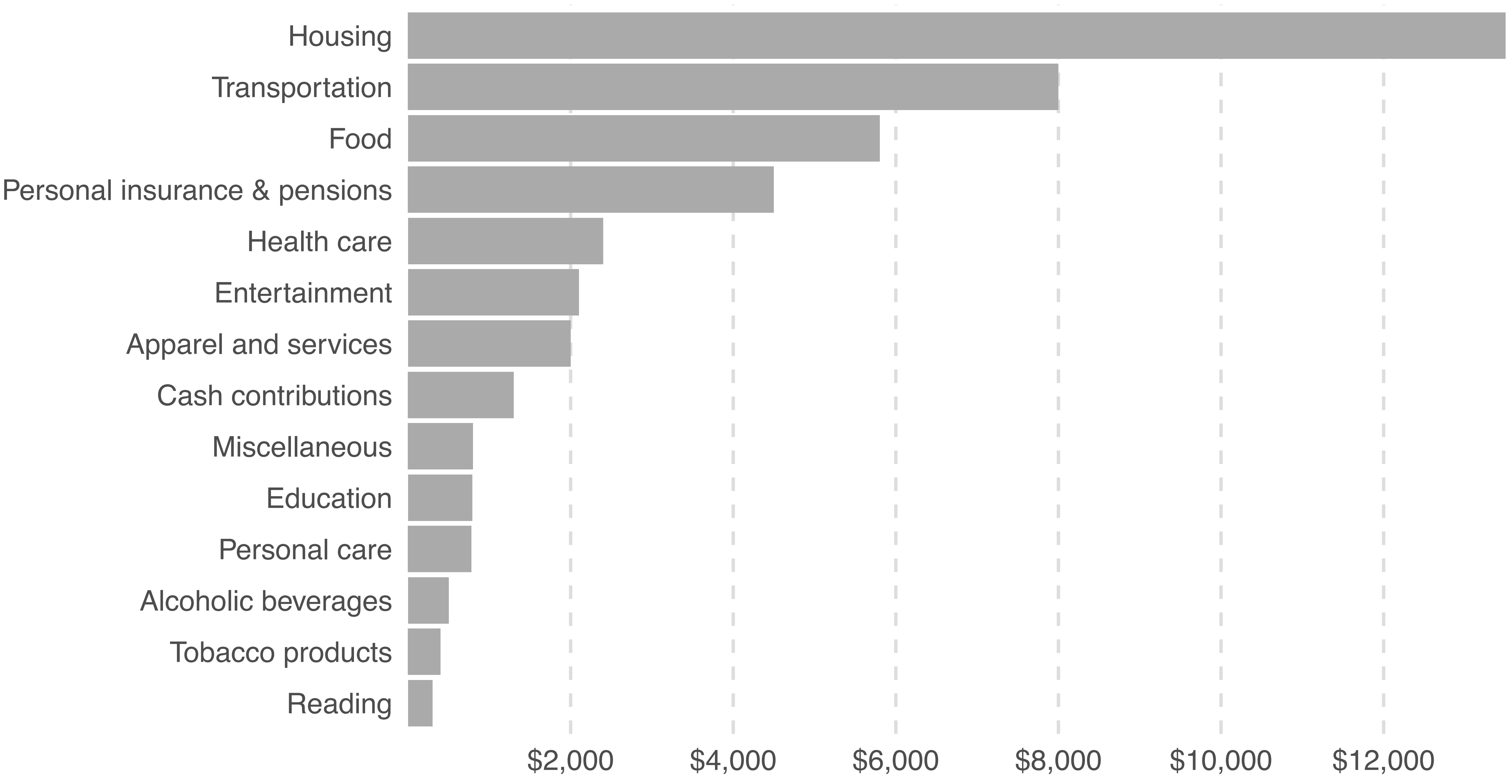

Fig. 3. Major categories of expenditures, descending dollar value, 2002 U.S. Consumer Expenditure Survey

While text can use different types of content structures, an abstract visualization just presents relationships between data points.

Thus, a single bar, map symbol or shape does not convey information. It only becomes meaningful by its relationship with other elements in the image—in other words, it is *polysemic:* **A data graphic acquires its meaning from comparison**.

— Koponen & Hildén, *The Data Visualization Handbook*

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why data graphics, **example data from Anscombe**

1		2		3		4	
x	y	x	y	x	y	x	y
10	8.04	10	9.14	10	7.46	8	6.58
8	6.95	8	8.14	8	6.77	8	5.76
13	7.58	13	8.74	13	12.74	8	7.71
9	8.81	9	8.77	9	7.11	8	8.84
11	8.33	11	9.26	11	7.81	8	8.47
14	9.96	14	8.10	14	8.84	8	7.04
6	7.24	6	6.13	6	6.08	8	5.25
4	4.26	4	3.10	4	5.39	19	12.50
12	10.84	12	9.13	12	8.15	8	5.56
7	4.82	7	7.26	7	6.42	8	7.91
5	5.68	5	4.74	5	5.73	8	6.89

why data graphics, example data from Anscombe

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summary statistics: *are the 4 data sets the same*?

	1		2		3		4	
	x	y	x	y	x	y	x	y
mean	9.00	7.50	9.00	7.50	9.00	7.50	9.00	7.50
sd	3.32	2.03	3.32	2.03	3.32	2.03	3.32	2.03

Parameter	Mean	Std Err	t-val	p-val
Dataset 1				
(Intercept)	3.000	1.125	2.667	0.026
x	0.500	0.118	4.241	0.002
Dataset 2				
(Intercept)	3.001	1.125	2.667	0.026
x	0.500	0.118	4.239	0.002
Dataset 3				
(Intercept)	3.002	1.124	2.670	0.026
x	0.500	0.118	4.239	0.002
Dataset 4				
(Intercept)	3.002	1.124	2.671	0.026
x	0.500	0.118	4.243	0.002

why data graphics, example data from Anscombe

1		2		3		4	
x	y	x	y	x	y	x	y
10	8.04	10	9.14	10	7.46	8	6.58
8	6.95	8	8.14	8	6.77	8	5.76
13	7.58	13	8.74	13	12.74	8	7.71
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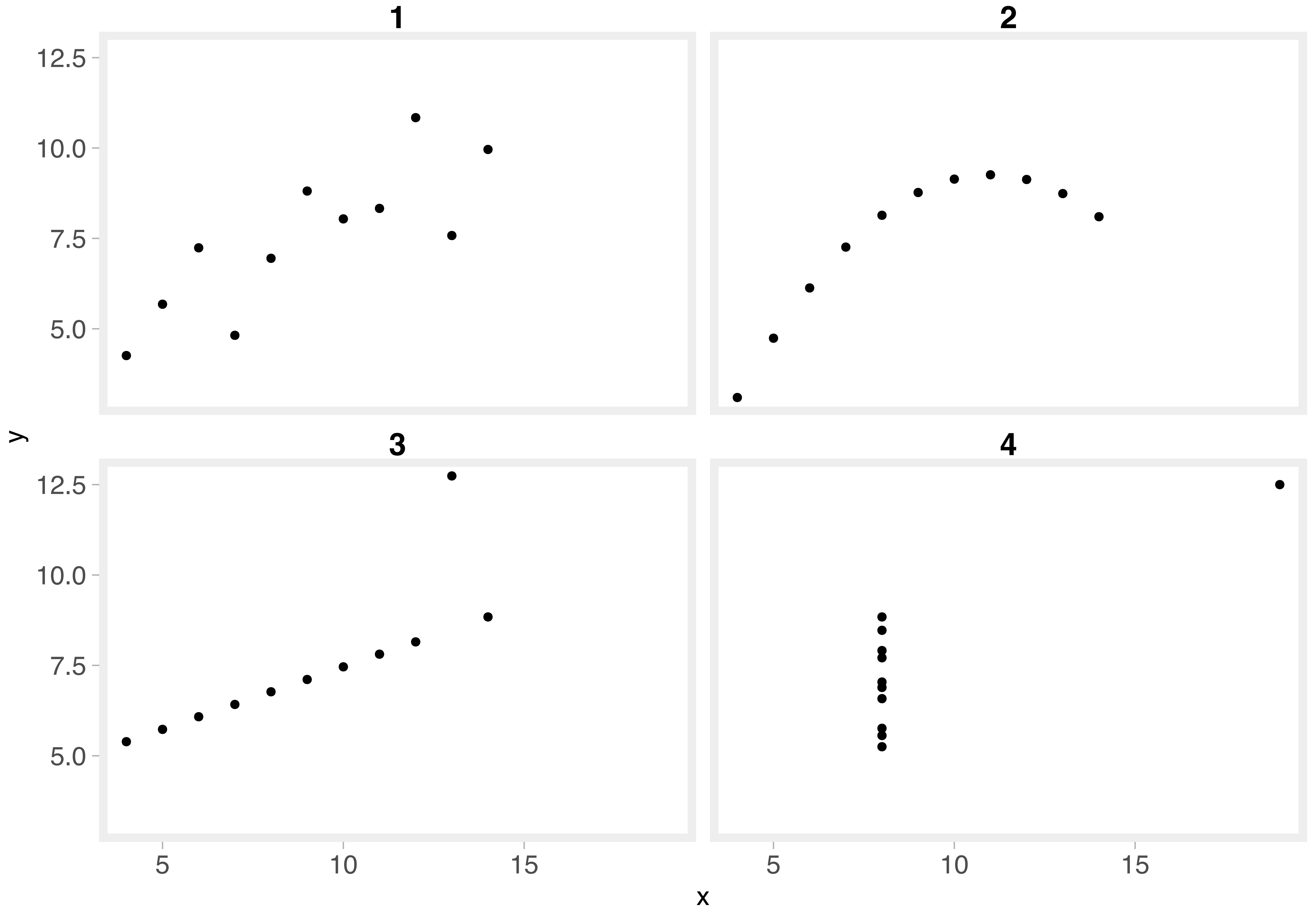
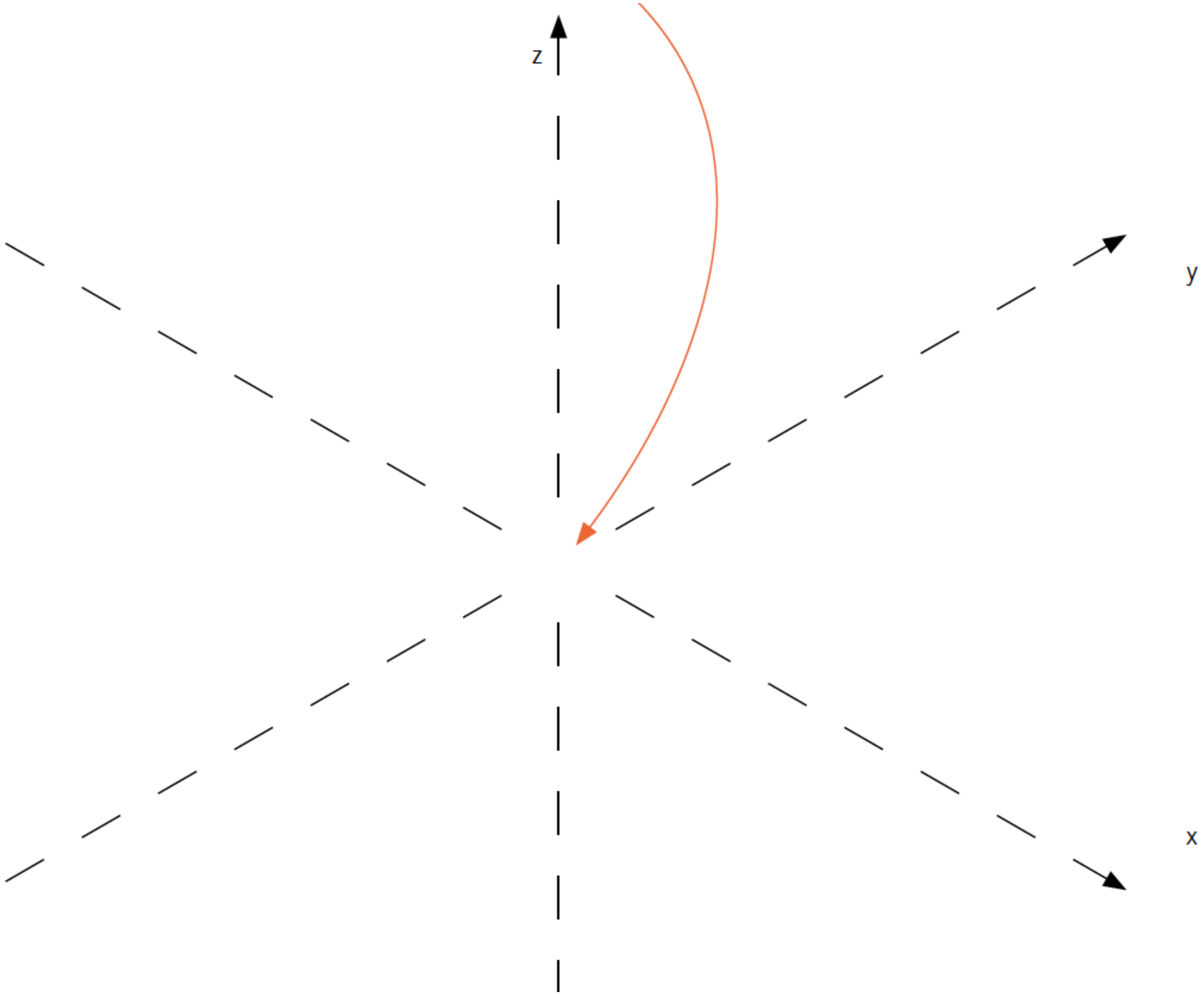
7	4.82	7	7.26	7	6.42	8	7.91
5	5.68	5	4.74	5	5.73	8	6.89

With graphics we can use our natural ability to see patterns through visual comparison

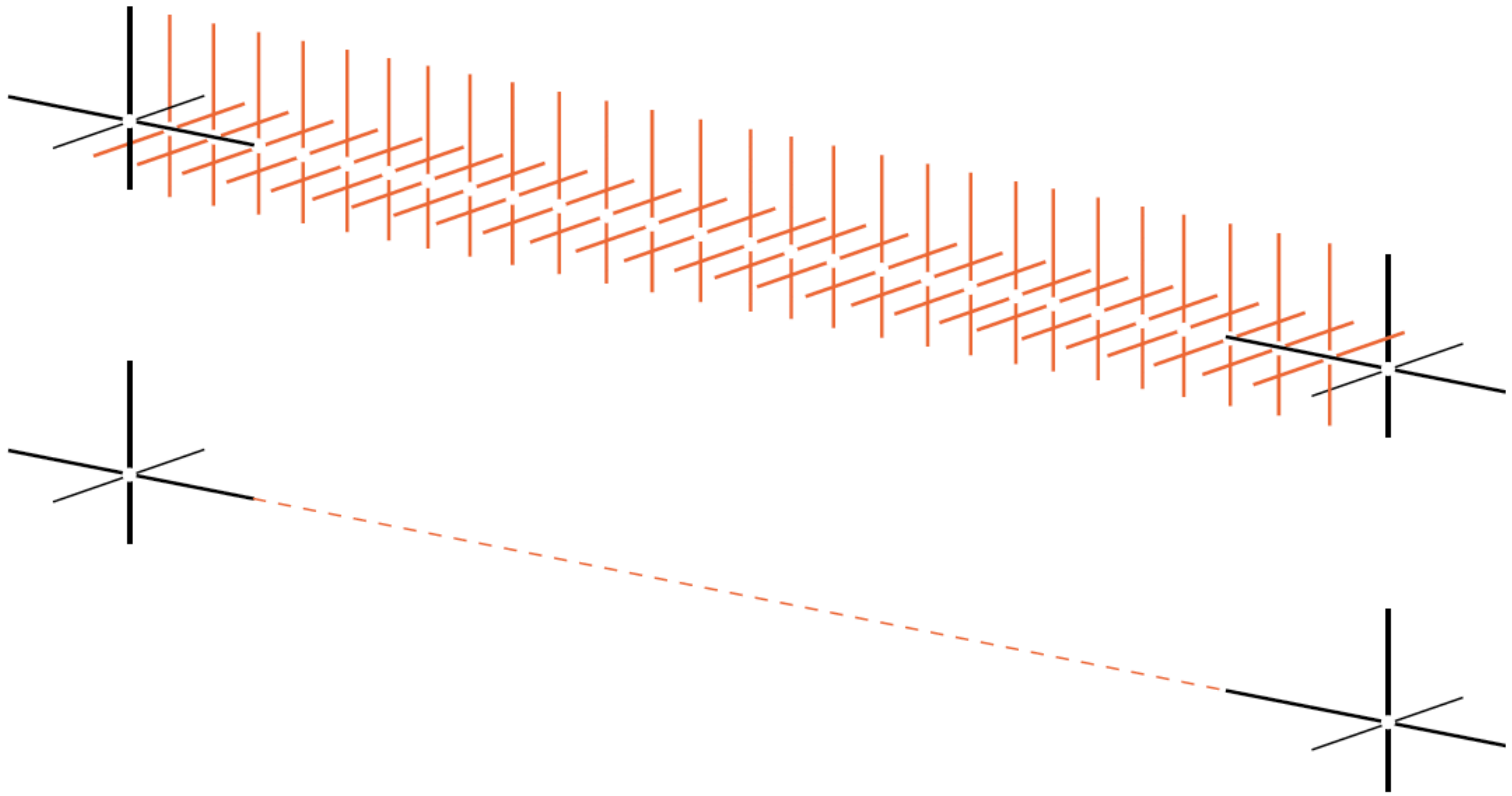


graphic design concepts

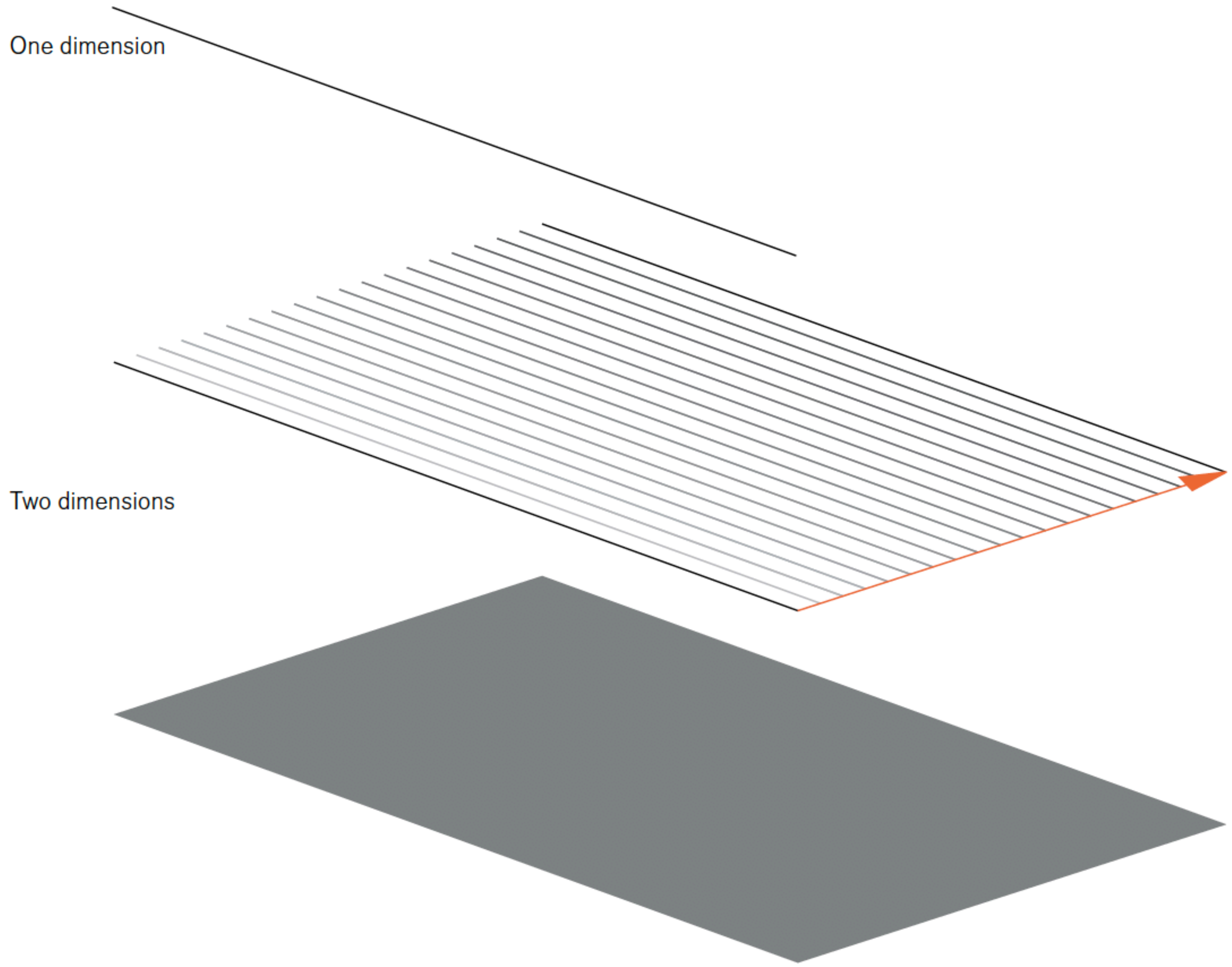
data encodings, geometry of graphical elements — point



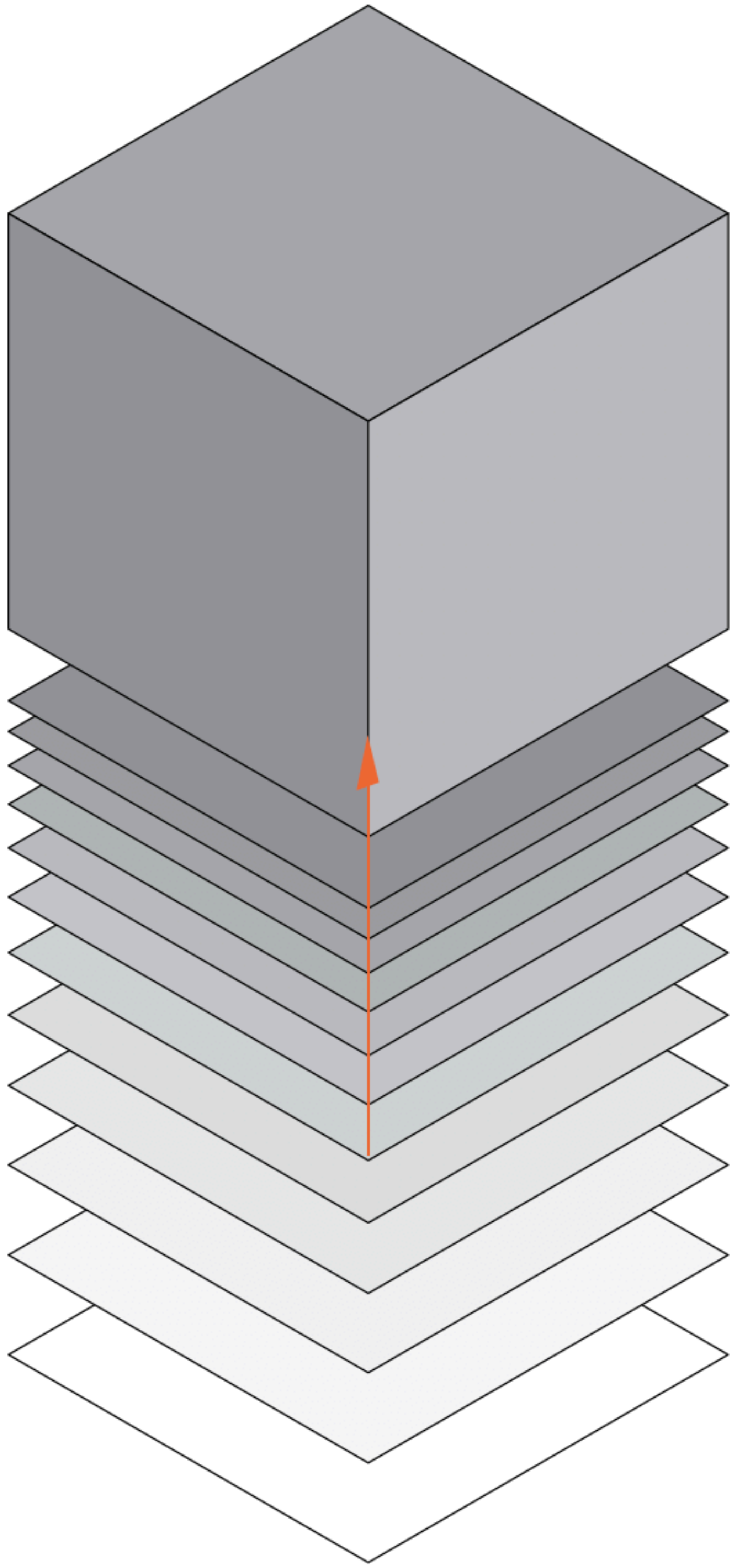
data encodings, geometry of graphical elements — line



data encodings, geometry of graphical elements — surface



data encodings, geometry of graphical elements — volume



data encodings, layering — order of elements determines position towards reader and when overlapping, occlude

```r
ggplot() +
  theme_void() +
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5, 5)) +
  geom_point(aes(x = 0, y = 0),
             size = 50, color = "orange") +
  geom_point(aes(x = 1, y = 1),
             size = 50, color = "dodgerblue")
```

```r
ggplot() +
  theme_void() +
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5, 5)) +
  geom_point(aes(x = 1, y = 1),
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  geom_point(aes(x = 0, y = 0),
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```
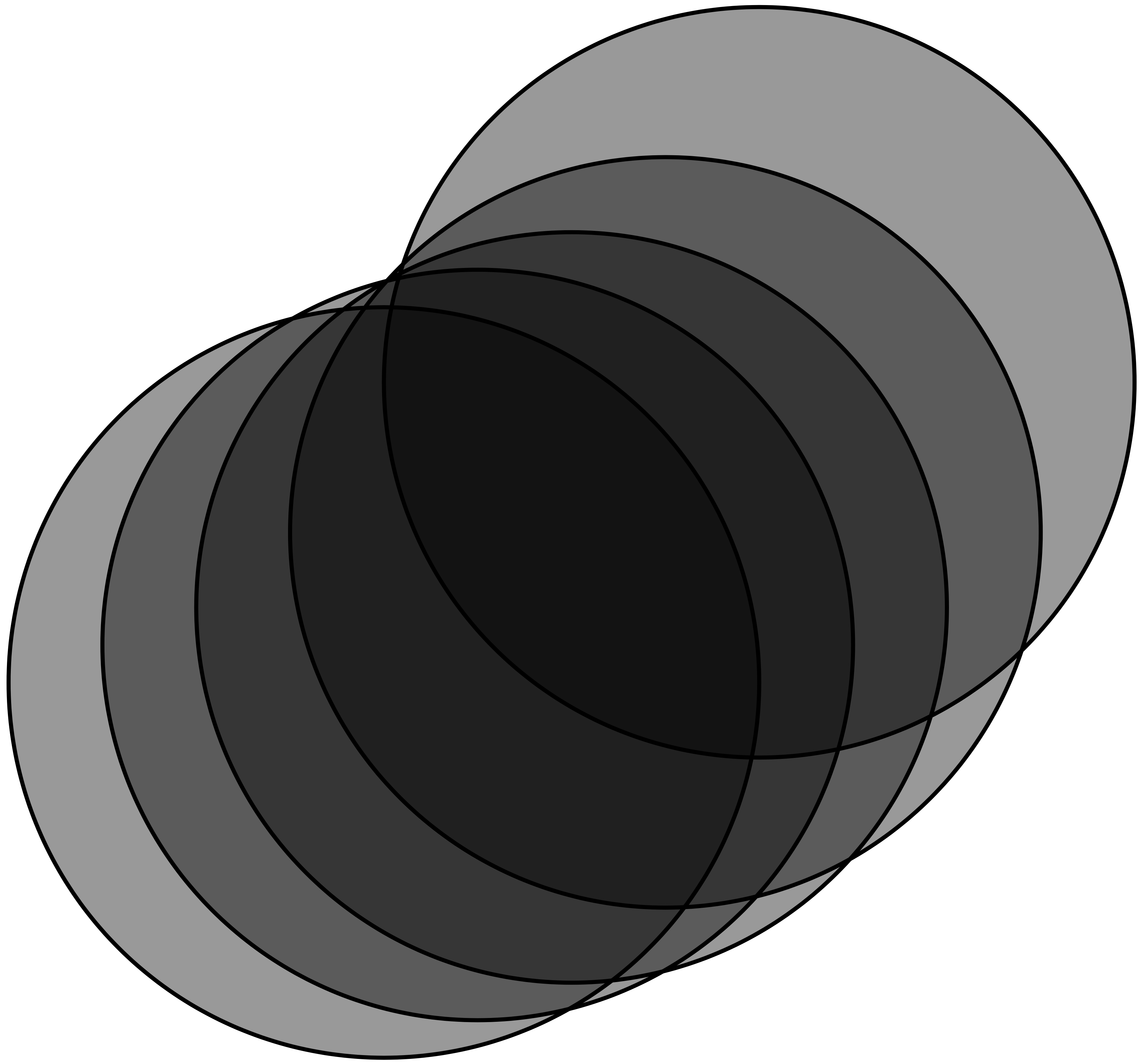
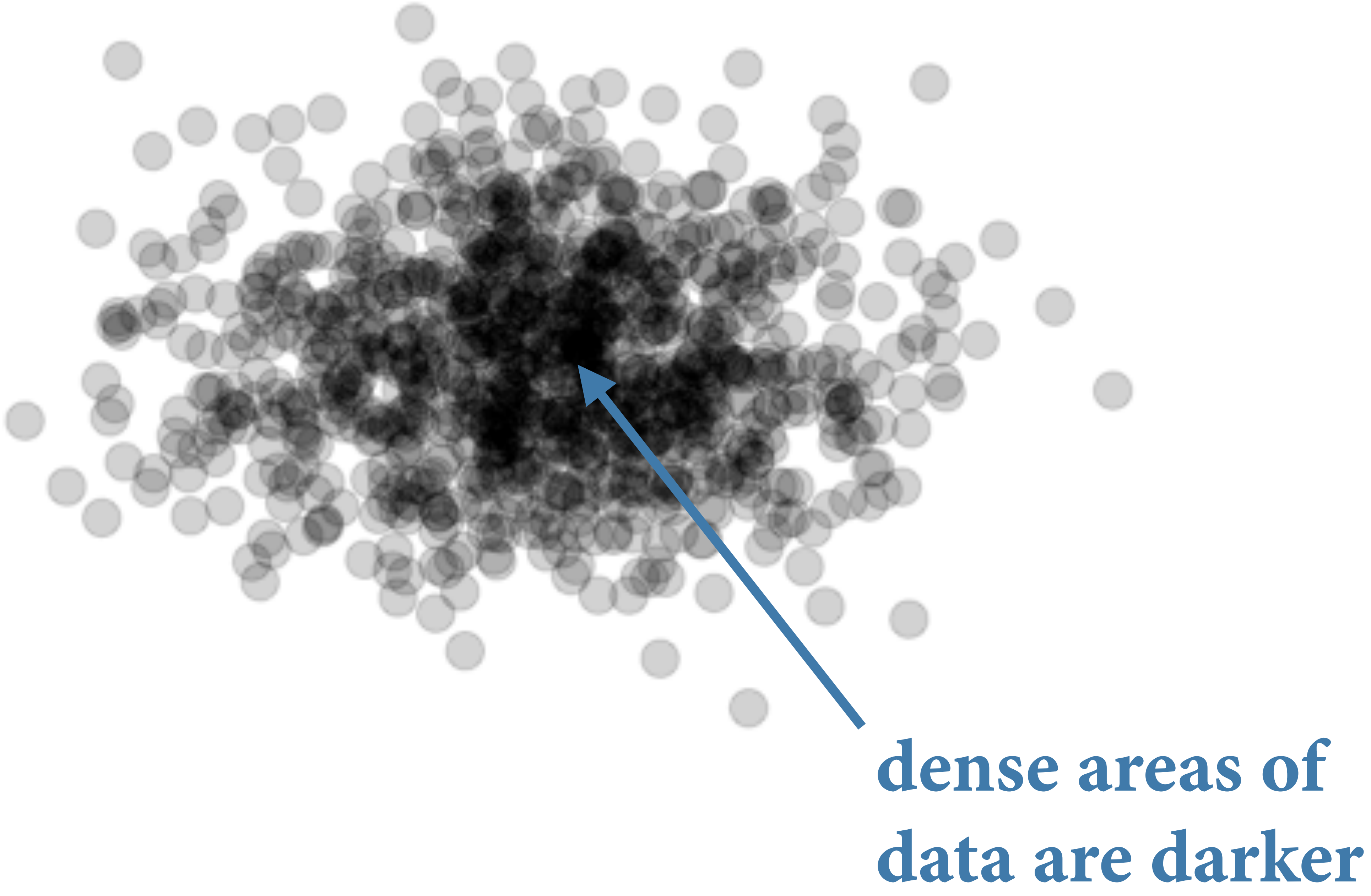

data encodings, layering — transparency (alpha) of *monochromes* can help us reason about the density of overlapping shapes

```
ggplot() +
  theme_void() +
  coord_equal() +
  ggforce::geom_circle(aes(
    x0 = seq(from = 0, to = 1, length.out = 5),
    y0 = c(0, .1, .2, .4, .8),
    r = 1
  ),
  fill = "#000000",
  alpha = 0.4)
```



data encodings, layering — transparency (alpha) of *monochromes* can help us reason about the density of overlapping shapes

```
x <- rnorm(1000)
y <- rnorm(1000)

ggplot() +
  theme_void() +
  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5, 5)) +
  geom_point(aes(x = x, y = y),
             size = 4, color = "black",
             alpha = 0.2)
```



data encodings, layering — data encoded in *semi-transparent hues*, if overlapping, are affected by transparency!

```
ggplot() +
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  scale_x_continuous(limits = c(-5, 5)) +
  scale_y_continuous(limits = c(-5, 5)) +
  geom_point(aes(x = 0, y = 0),
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             alpha = 0.4)
```
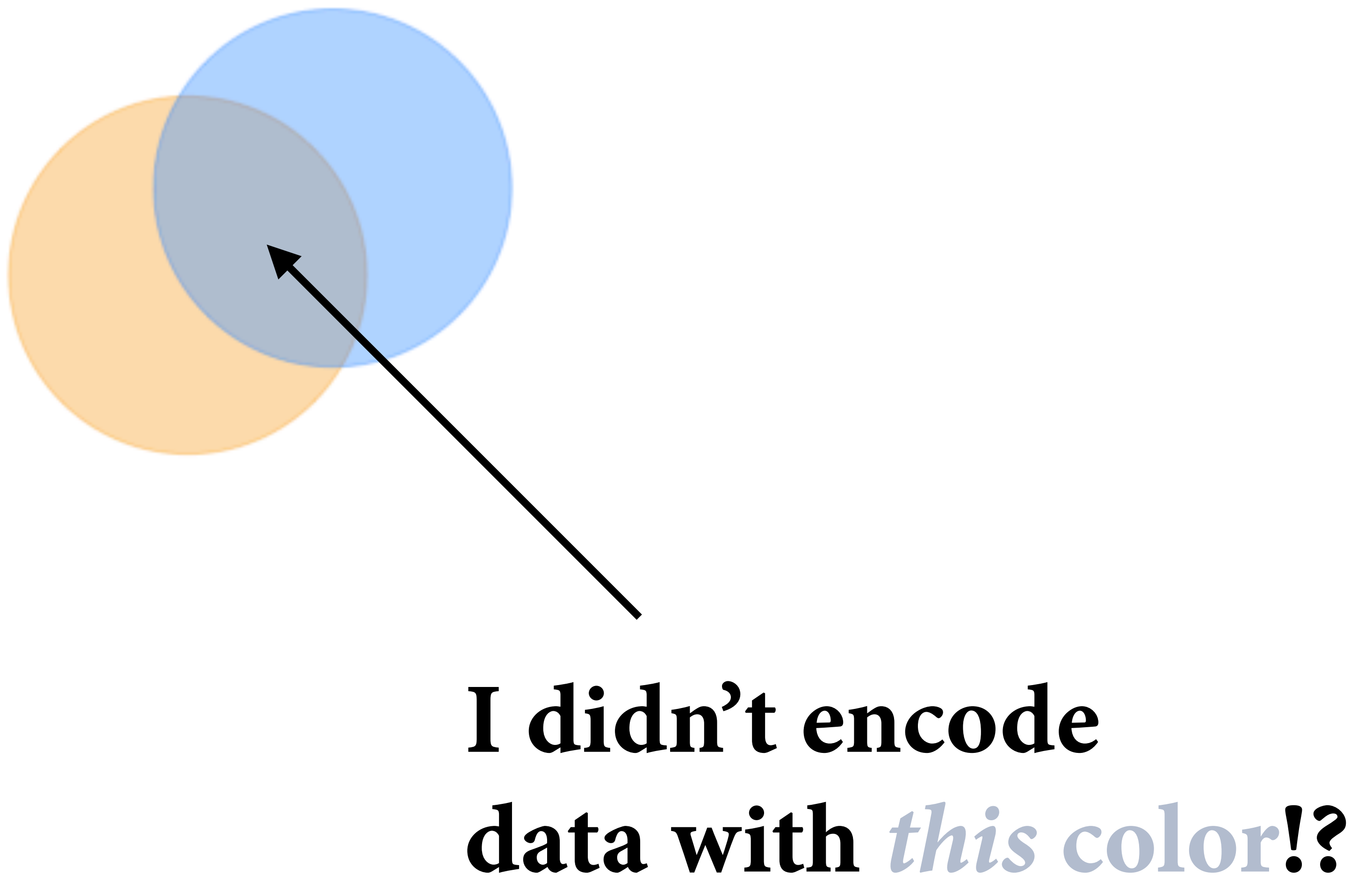
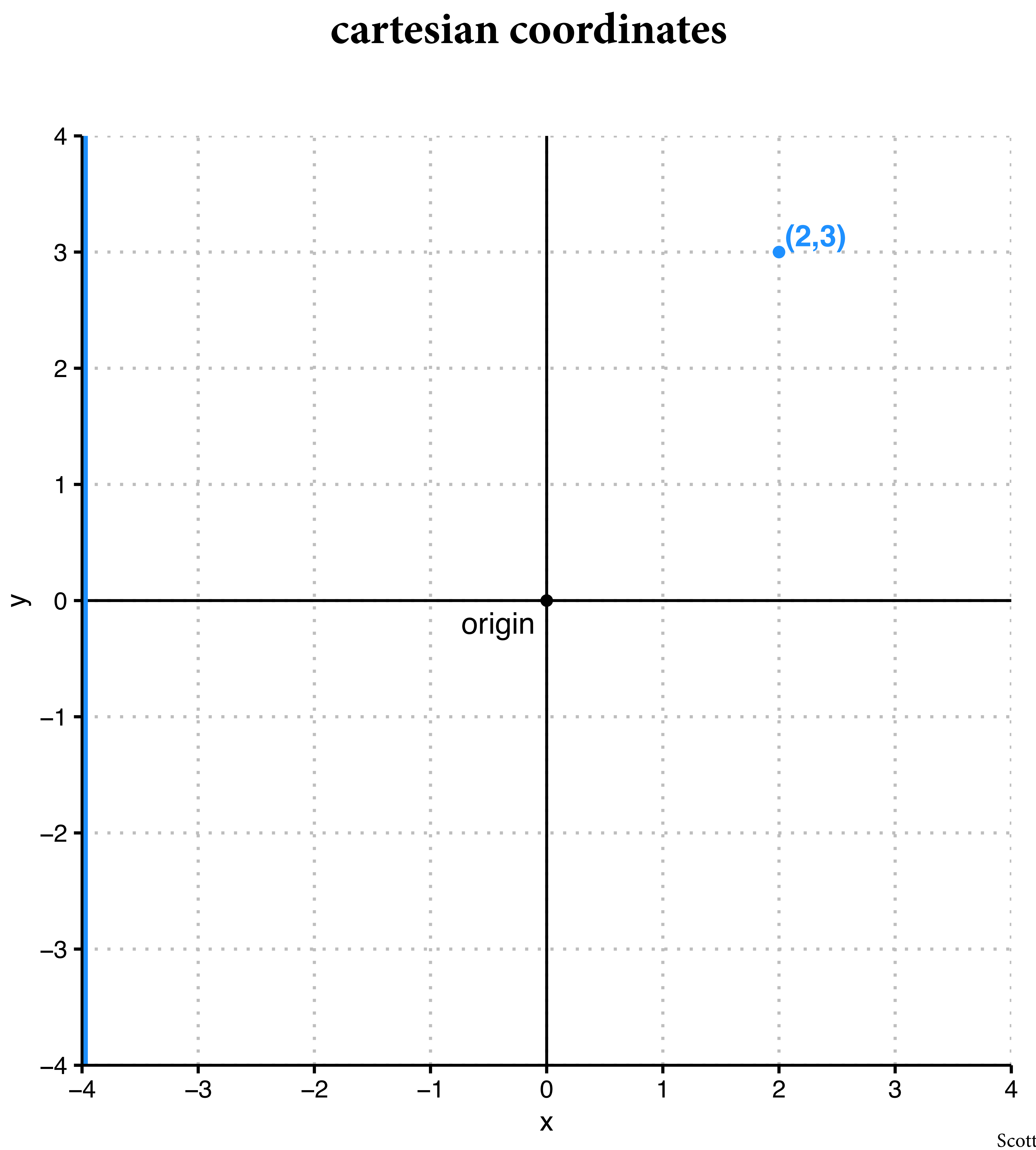



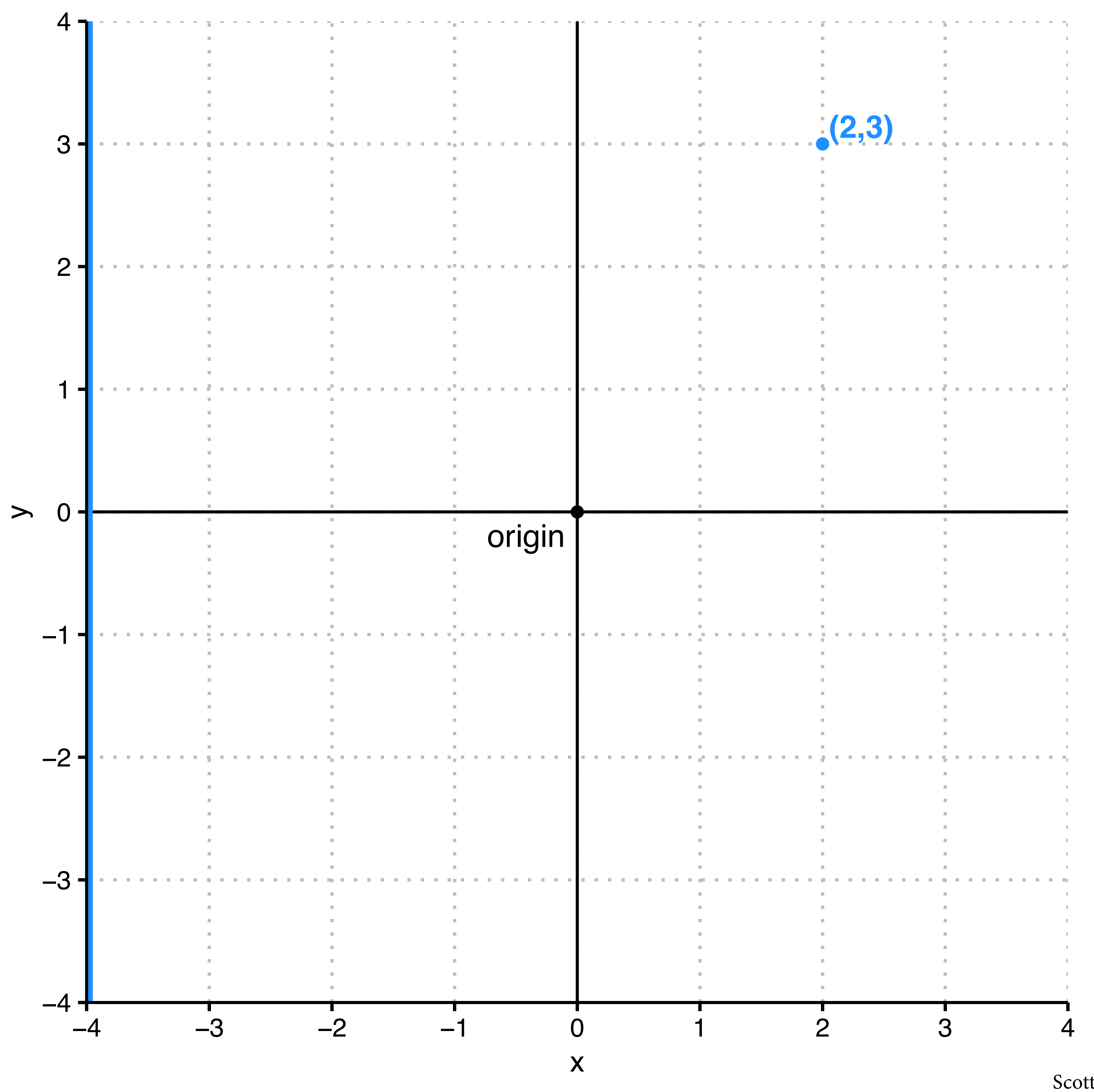
graphs — coordinate systems and scales

coordinates and scales, *two-dimensional Cartesian* coordinates — x and y axes run orthogonally to each other, and data values placed along linear axes

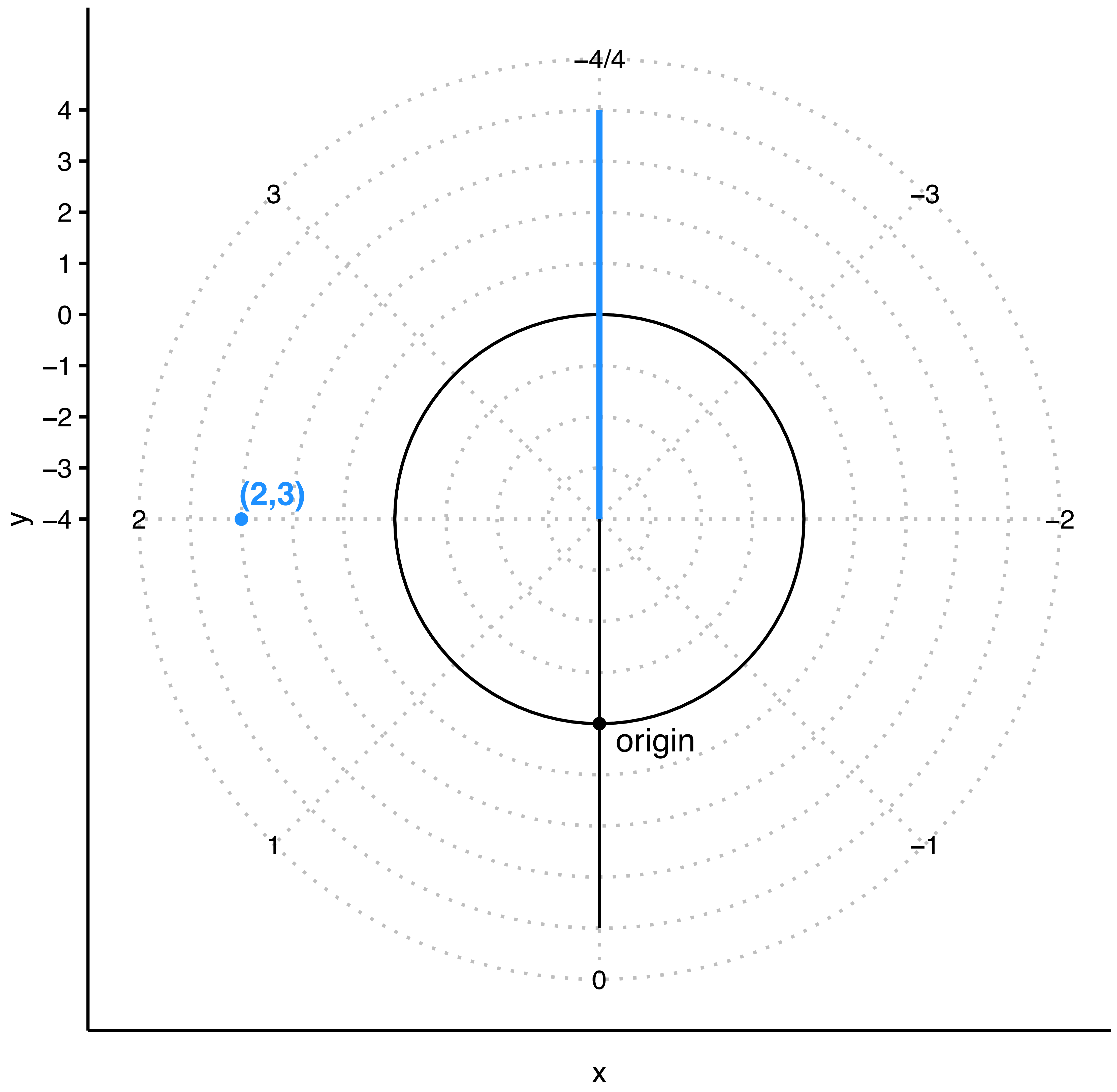


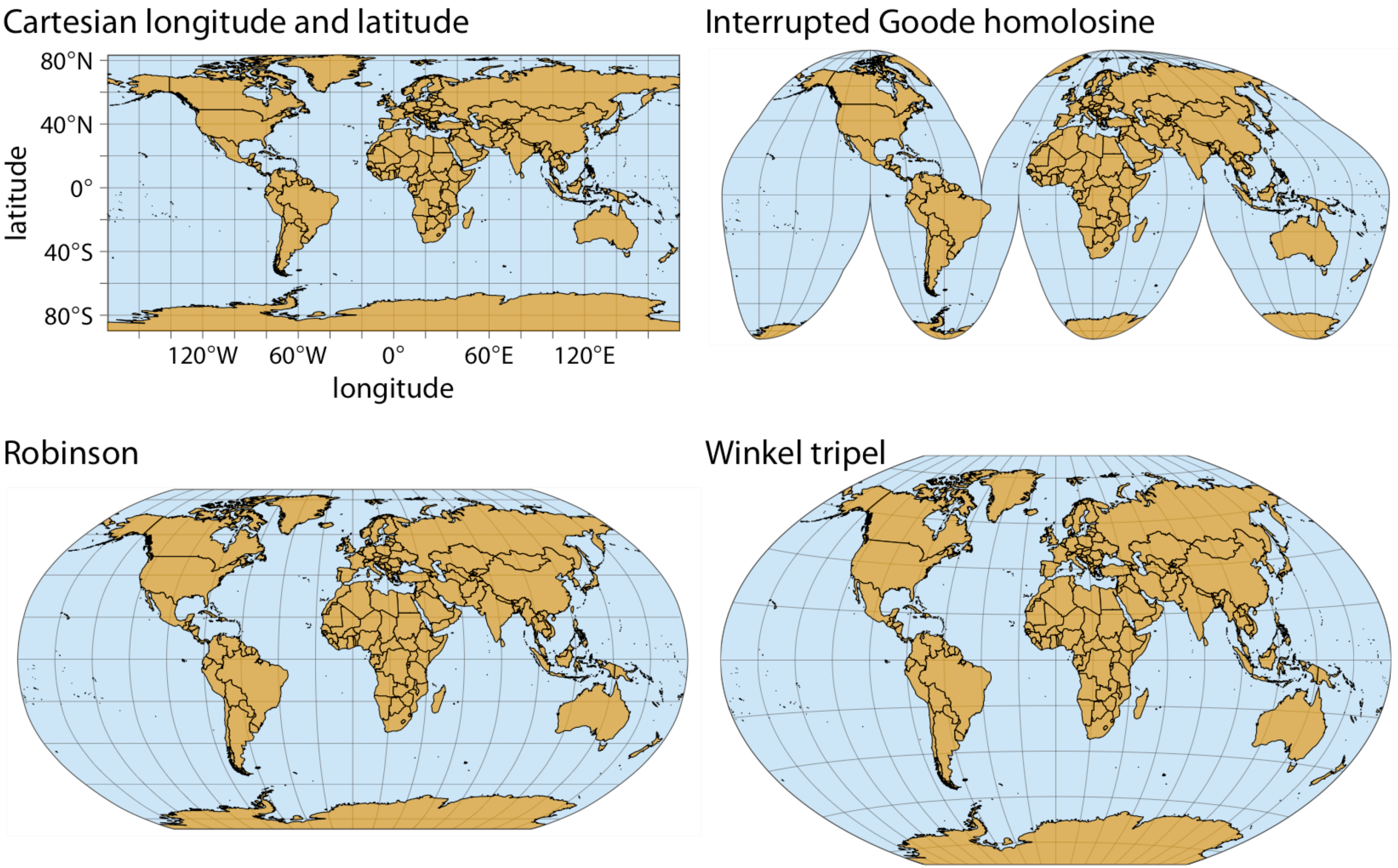
 ***other* coordinate systems are sometimes more effective in conveying information**

cartesian coordinates



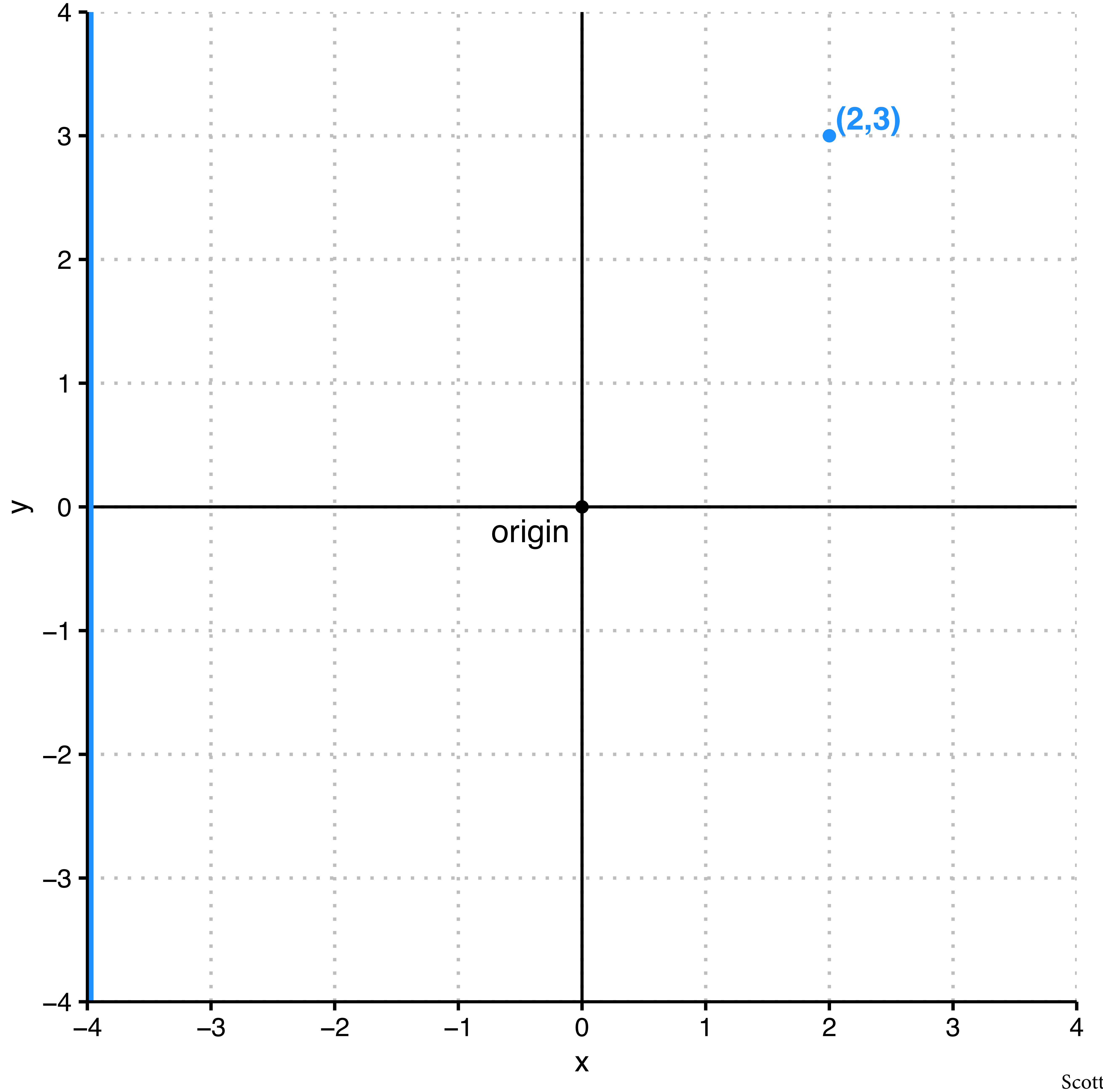
polar coordinates



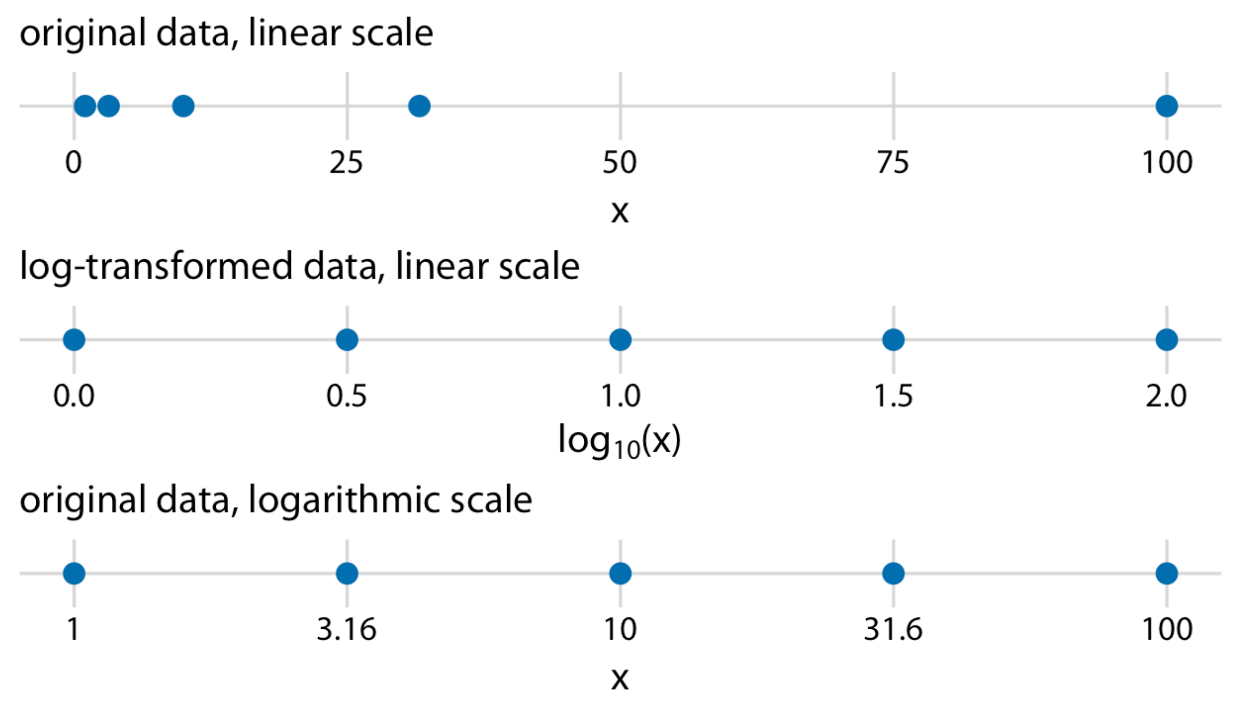

Cartesian longitude and latitude
80°N
40°N
0°
40°S
80°S
latitude
120°W
60°W
0°
60°E
120°E
longitude
Interrupted Goode homolosine
Robinson
Winkel tripel

coordinates and scales, as with choosing coordinates, we can *transform* ***scales for data or axes*** for better understanding

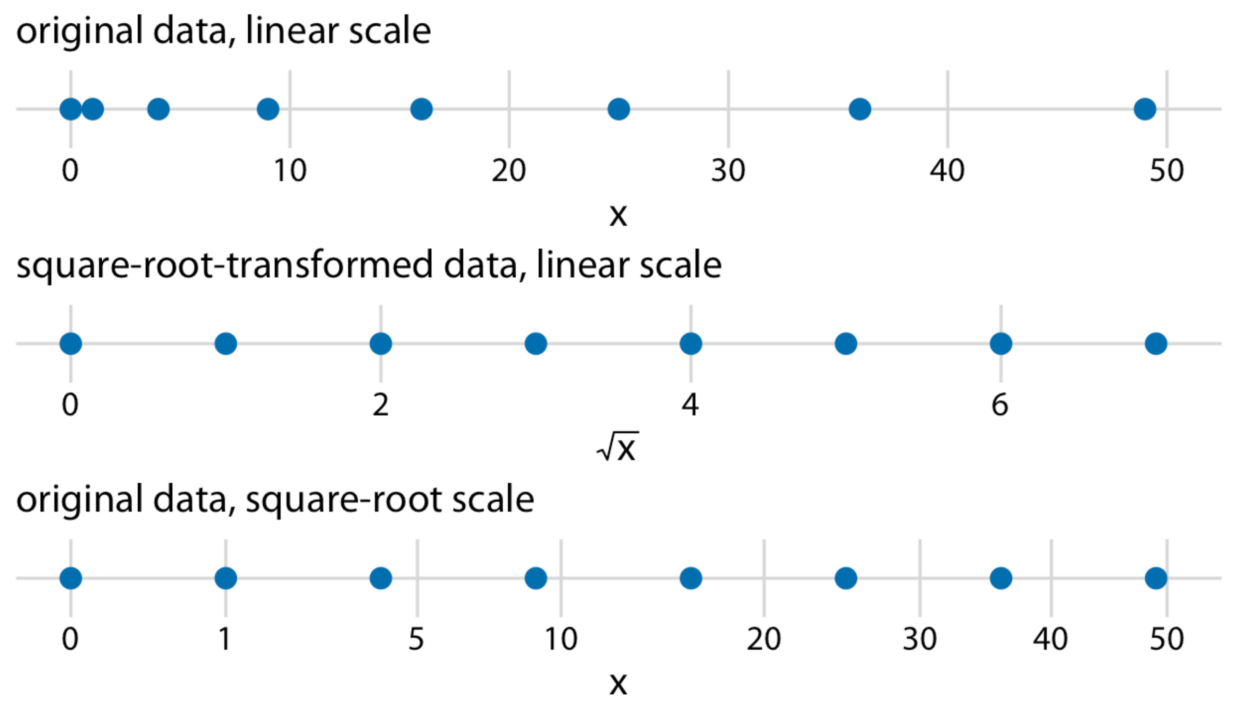
linear ***scales*** on cartesian coordinates



example — *log transforms*

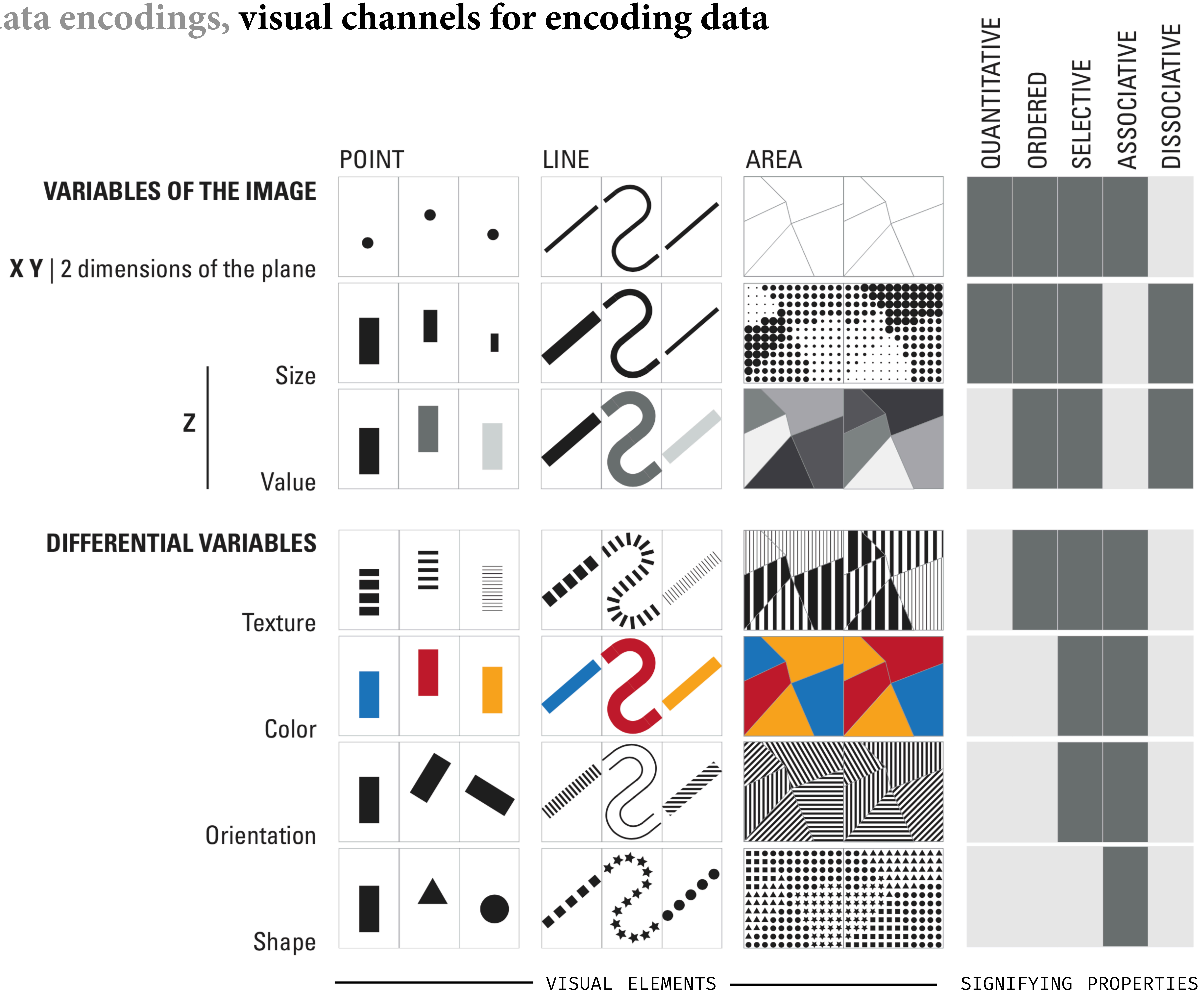


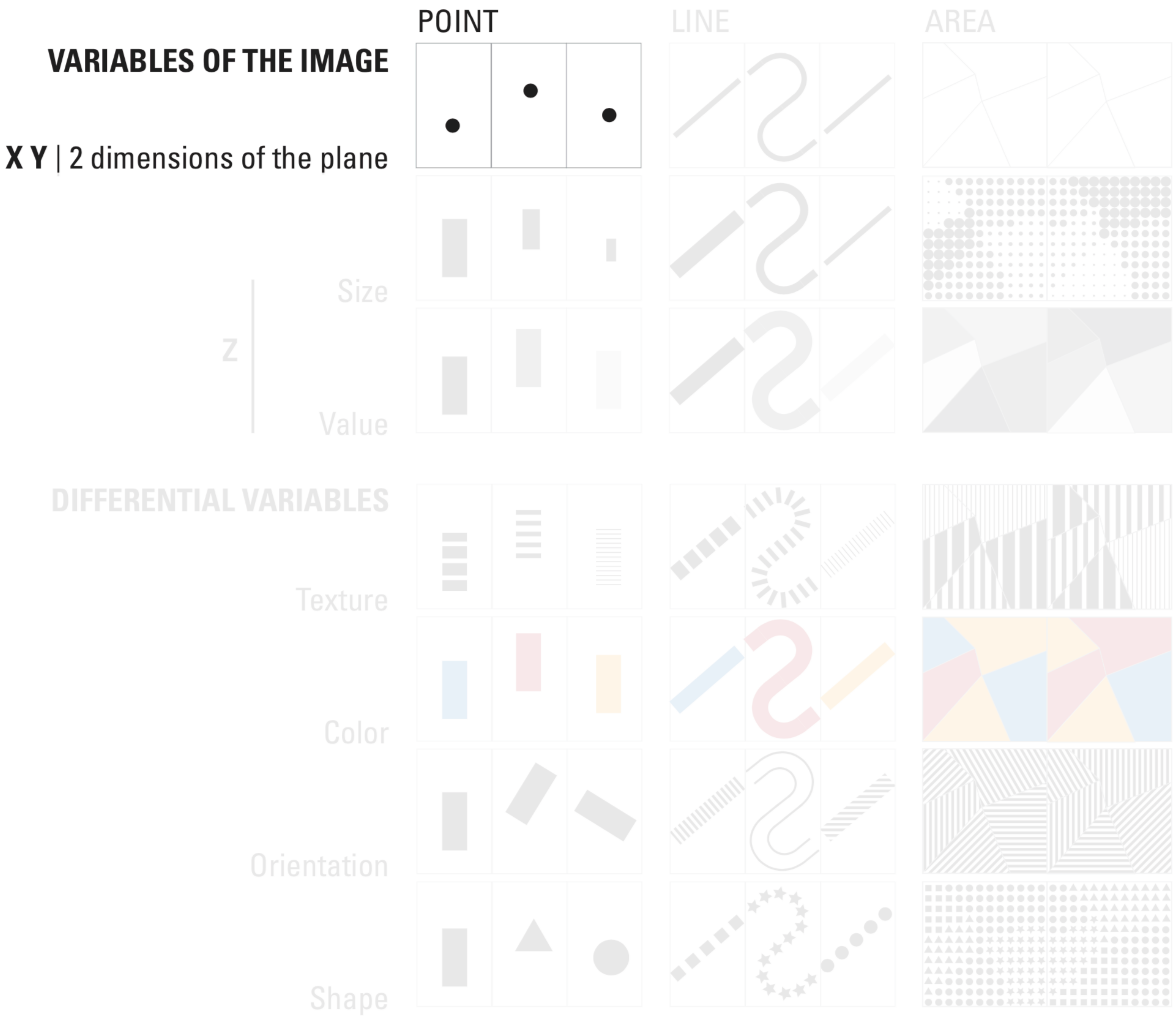
example — *square-root transforms*



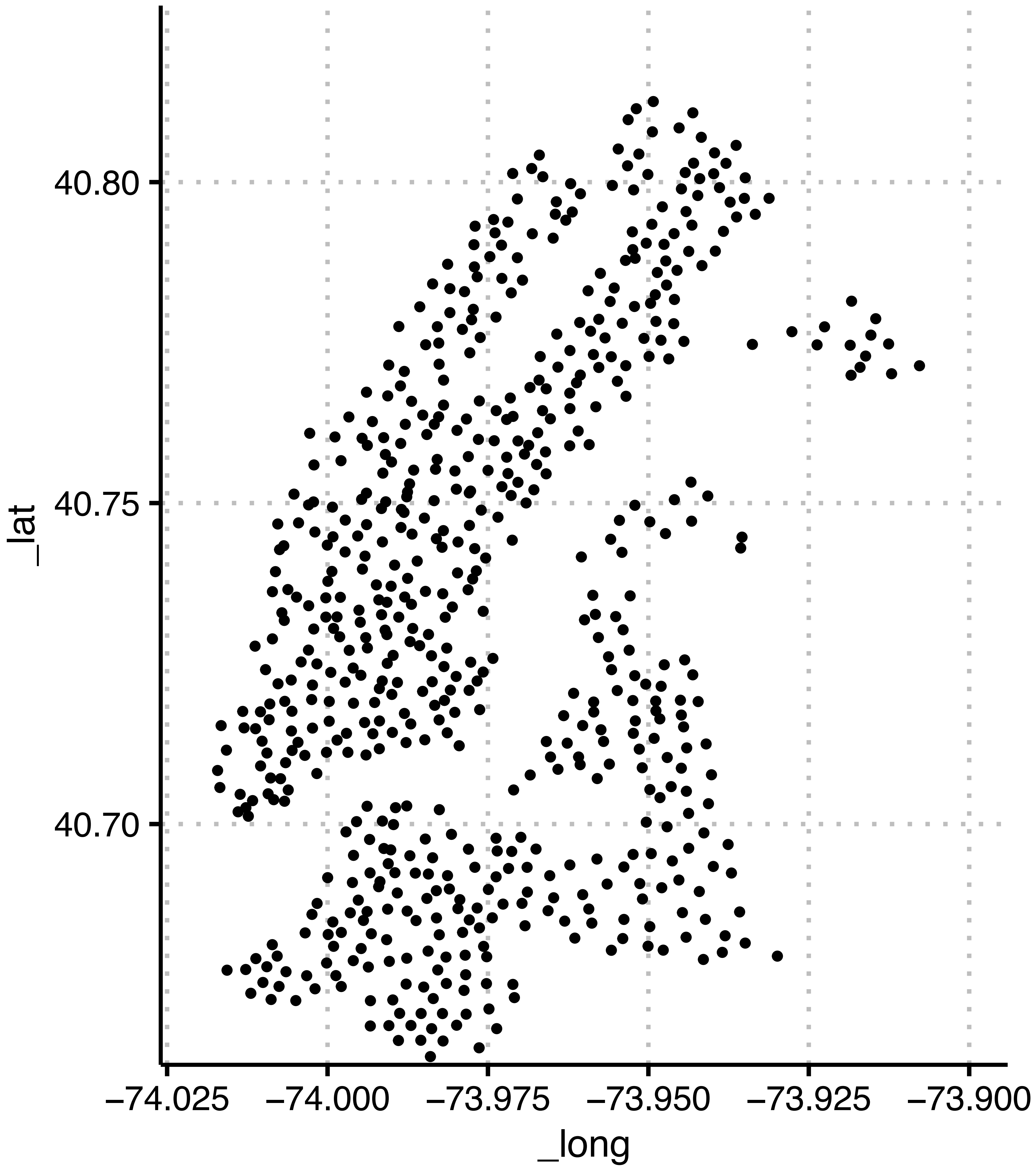
data encodings for visual comparison

data encodings, visual channels for encoding data





Citi Bike example — *exploratory data analysis*



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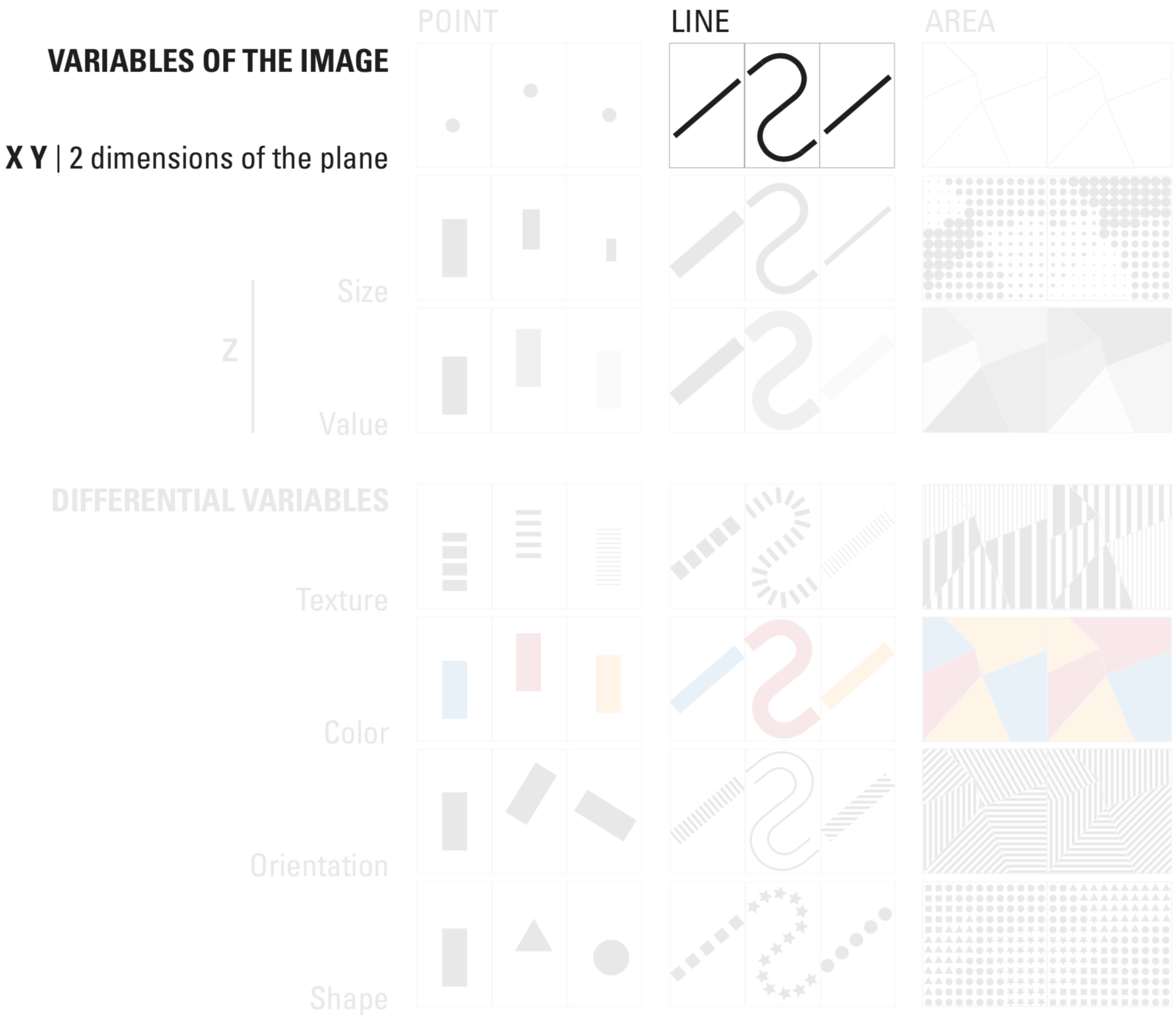

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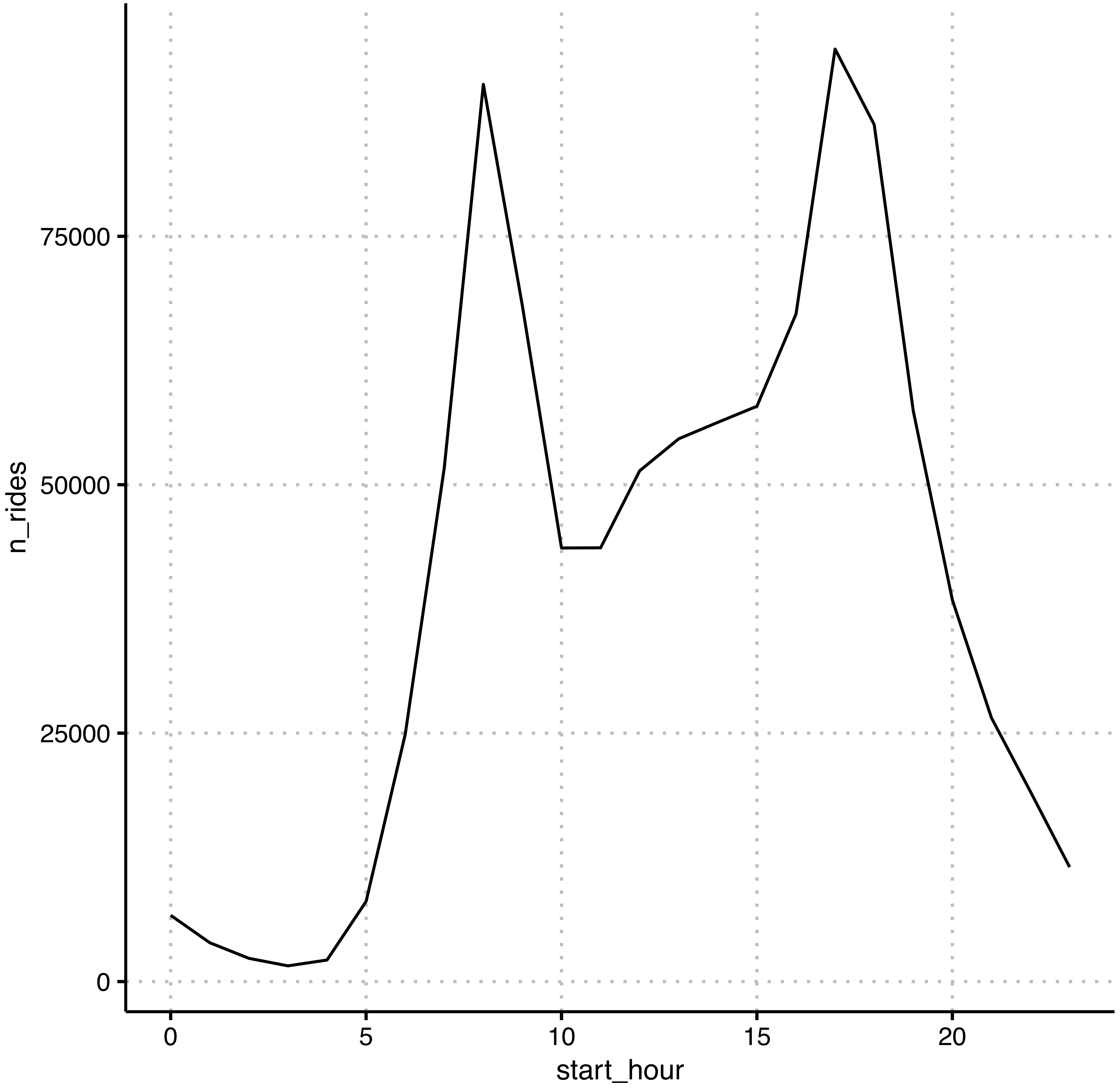

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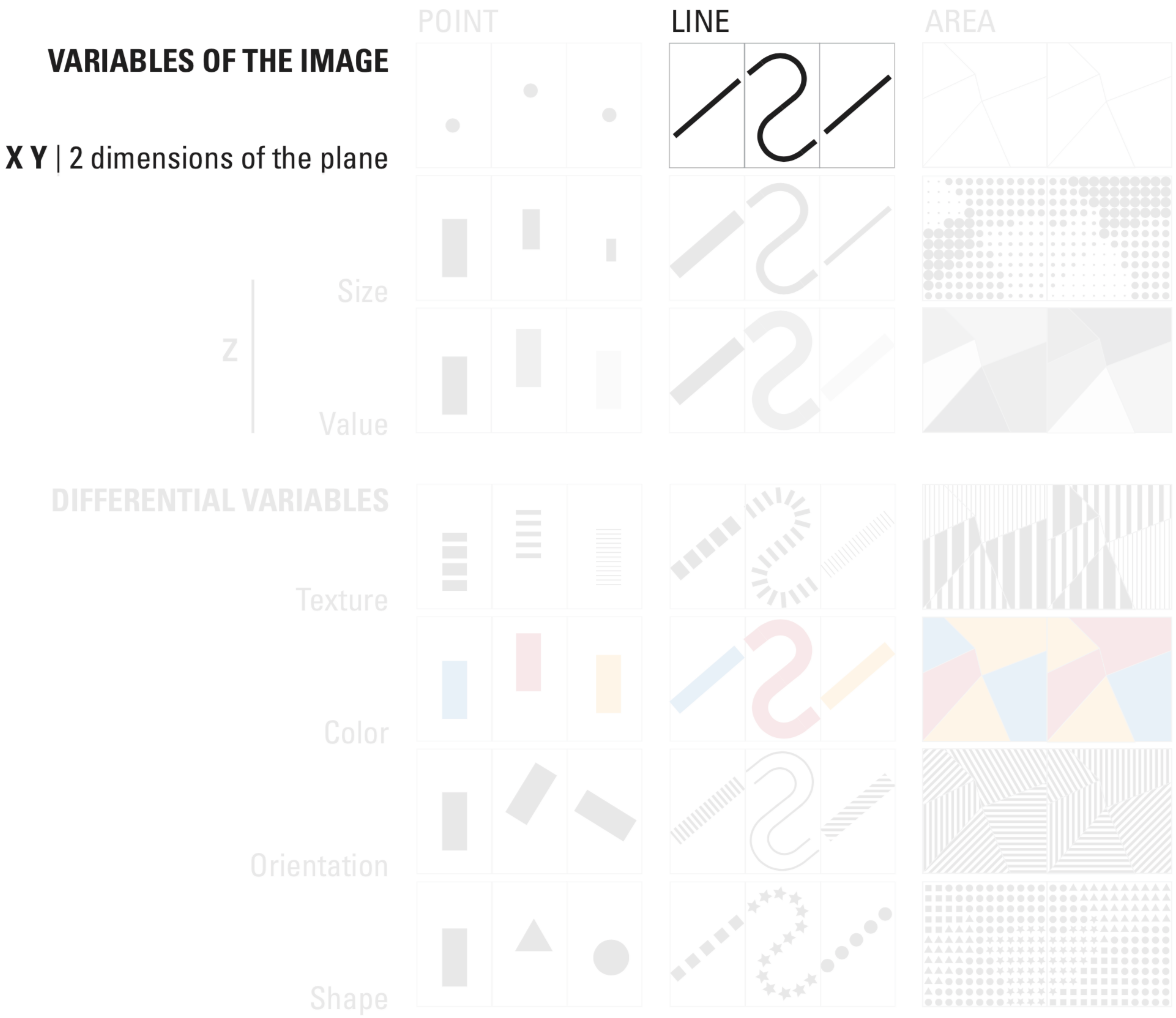

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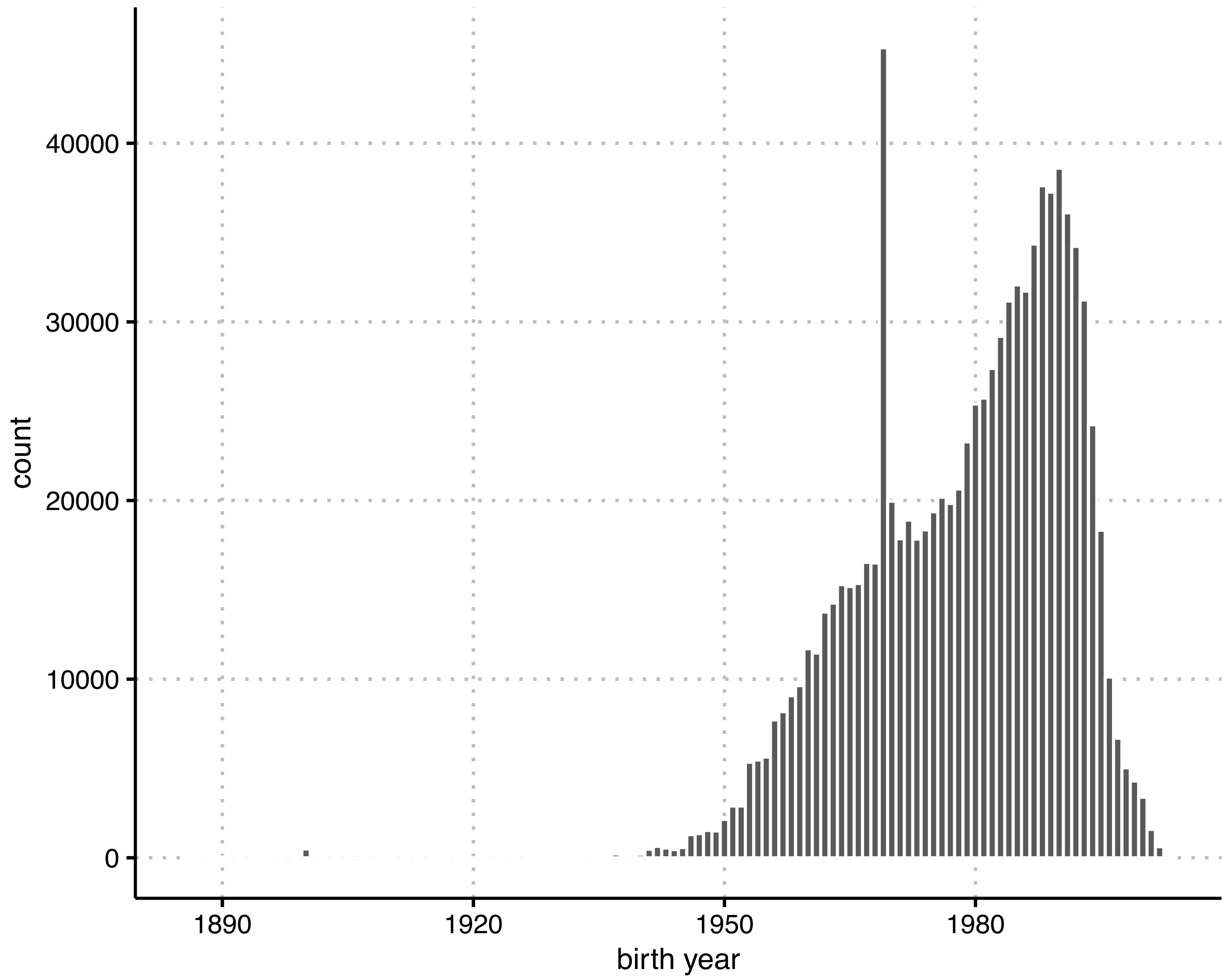

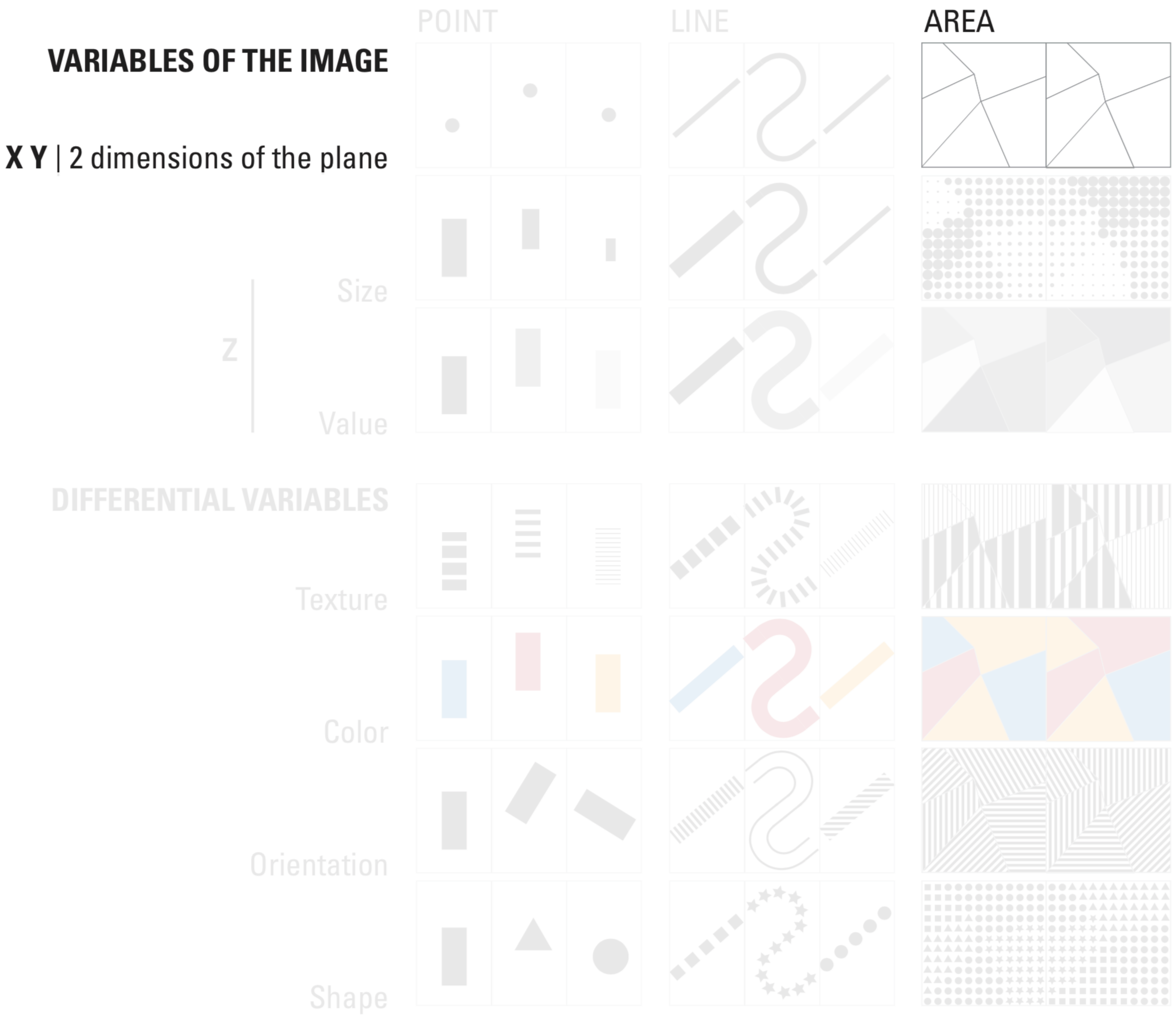

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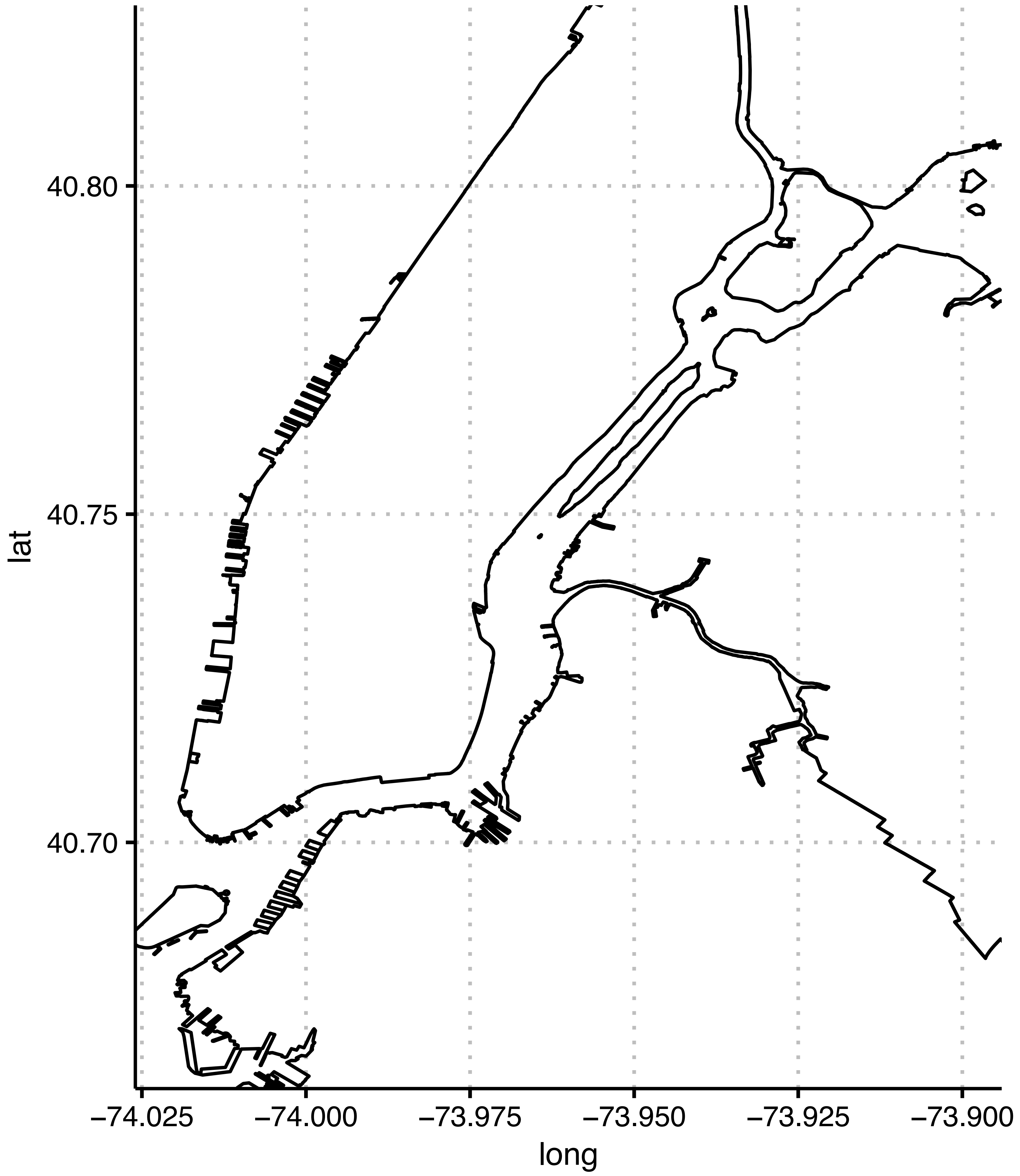

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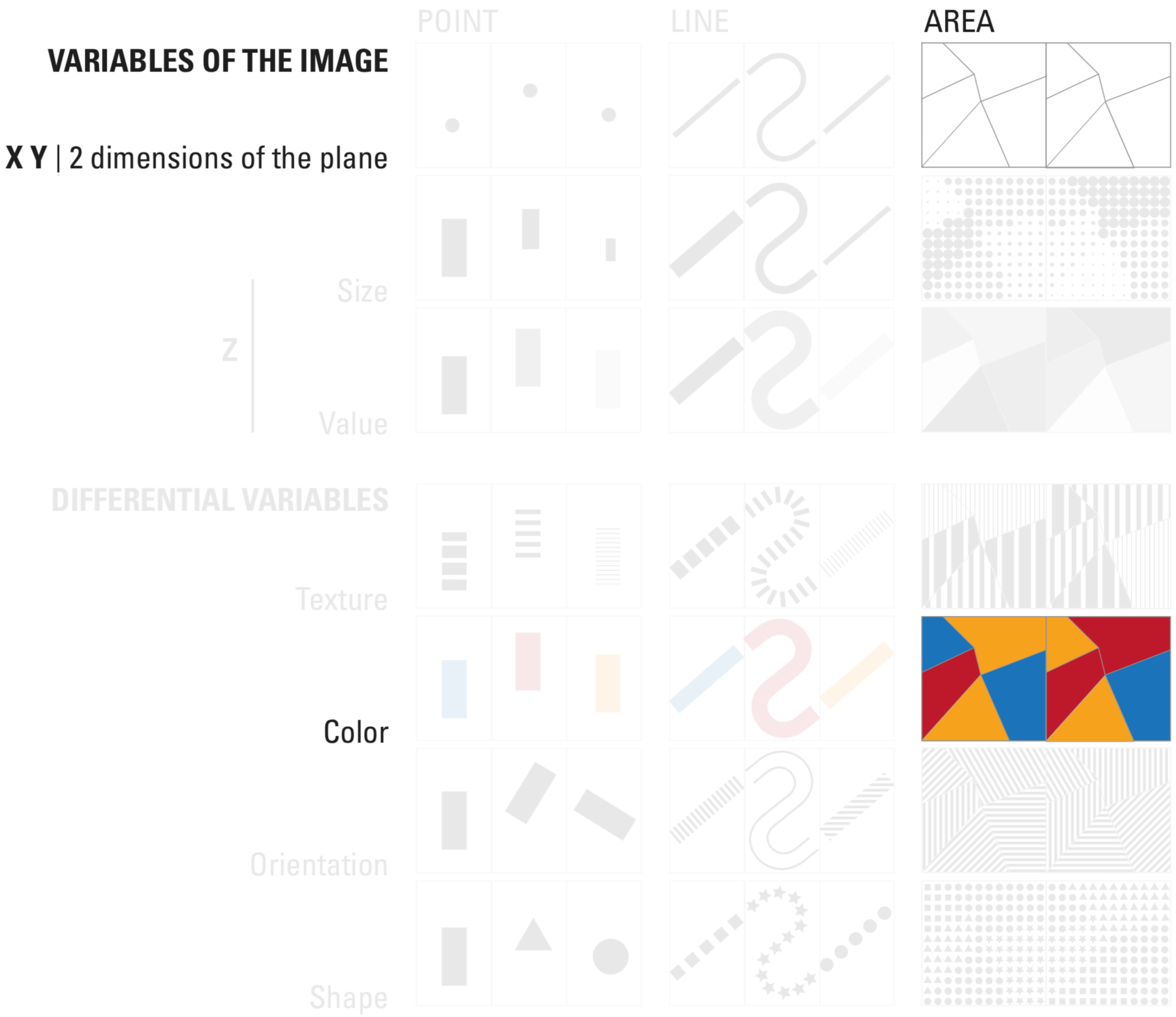

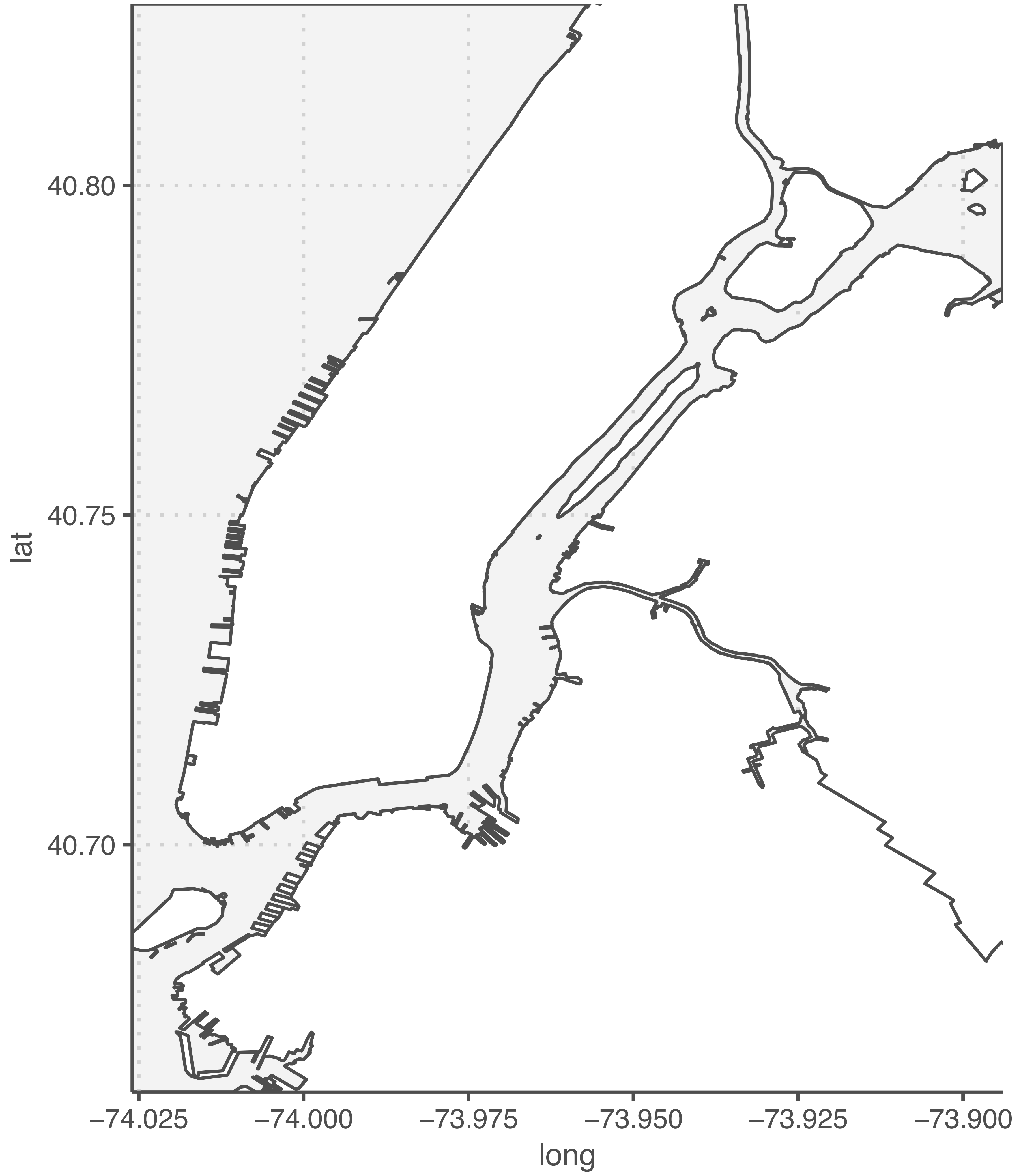

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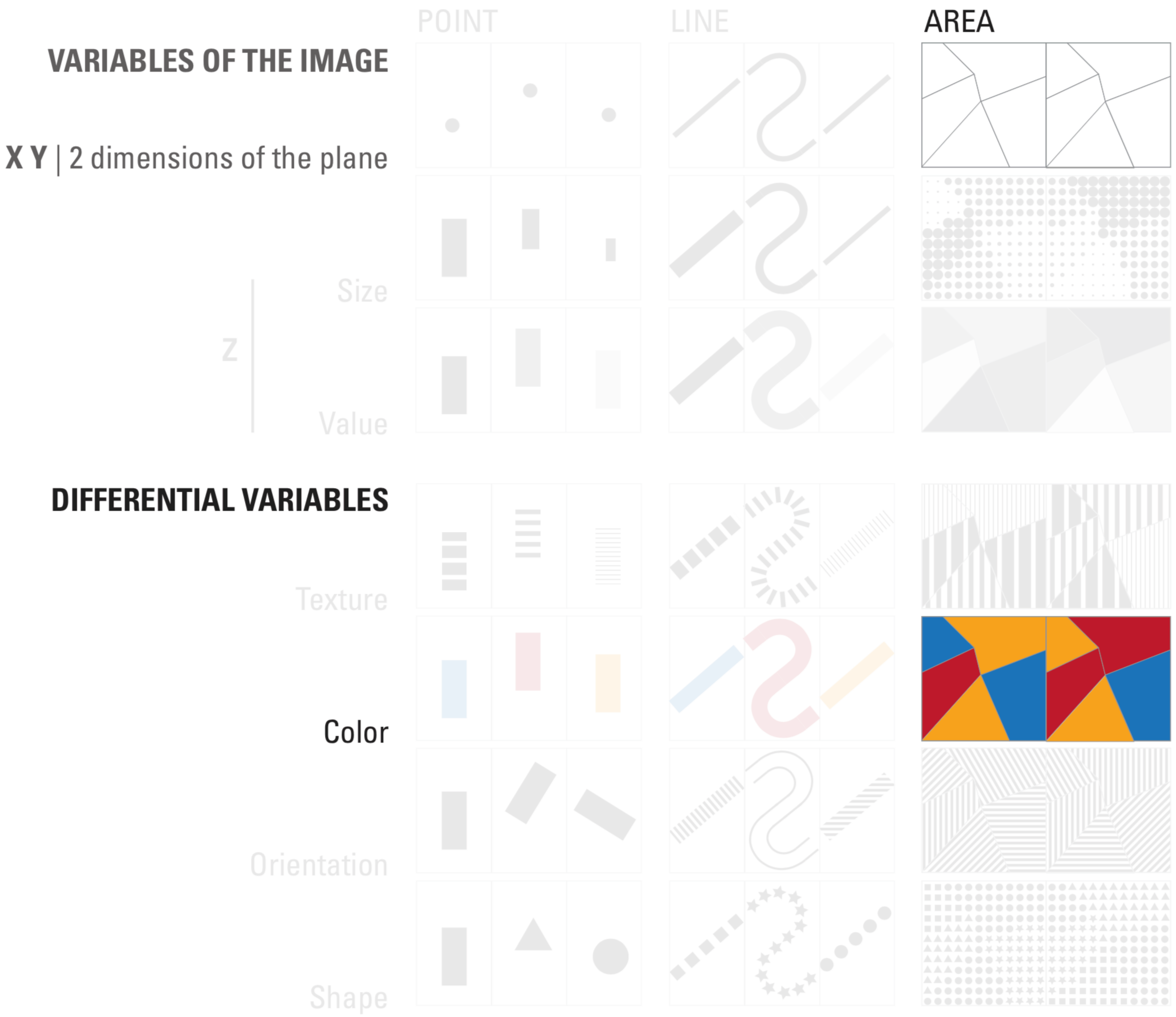

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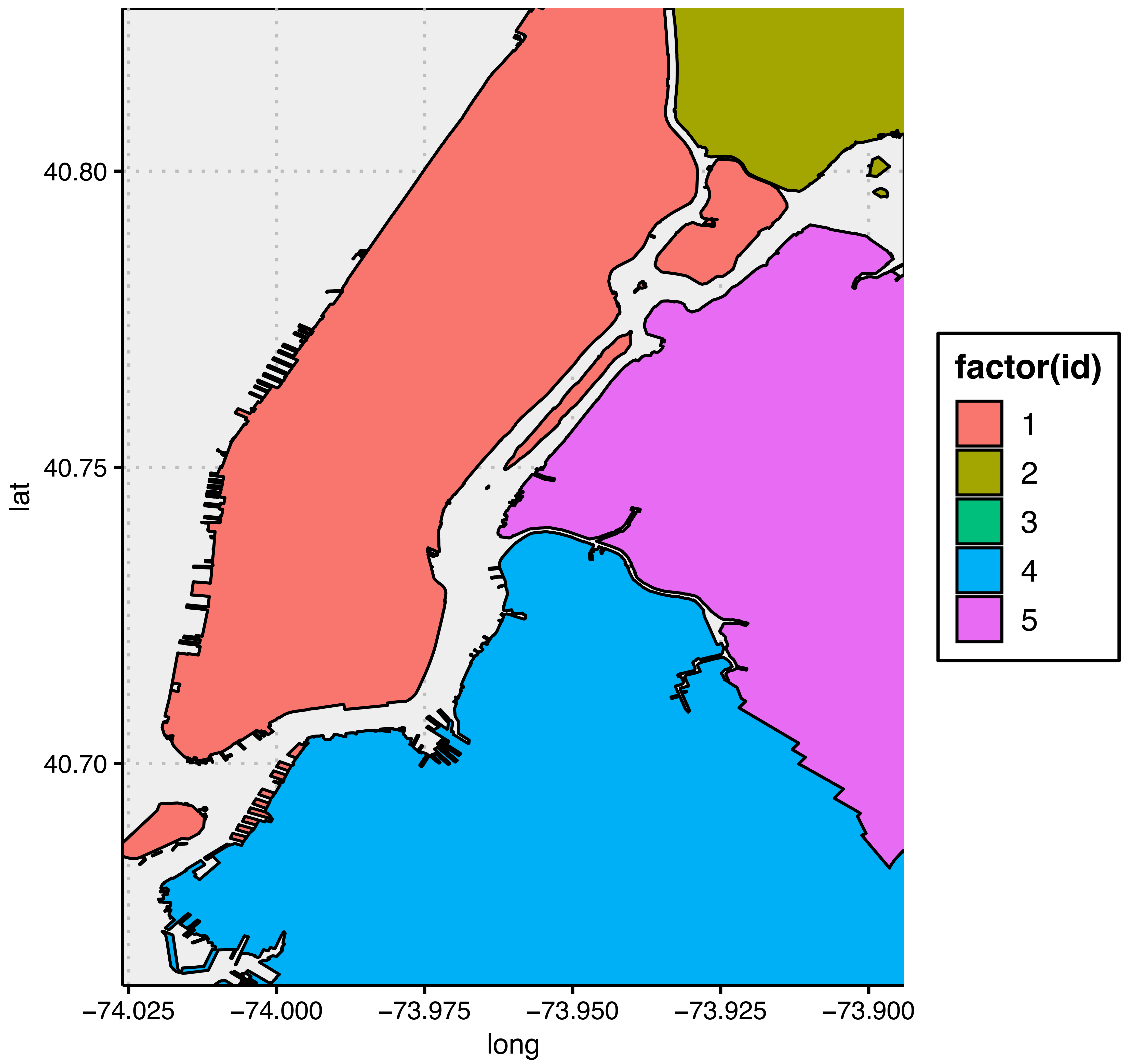
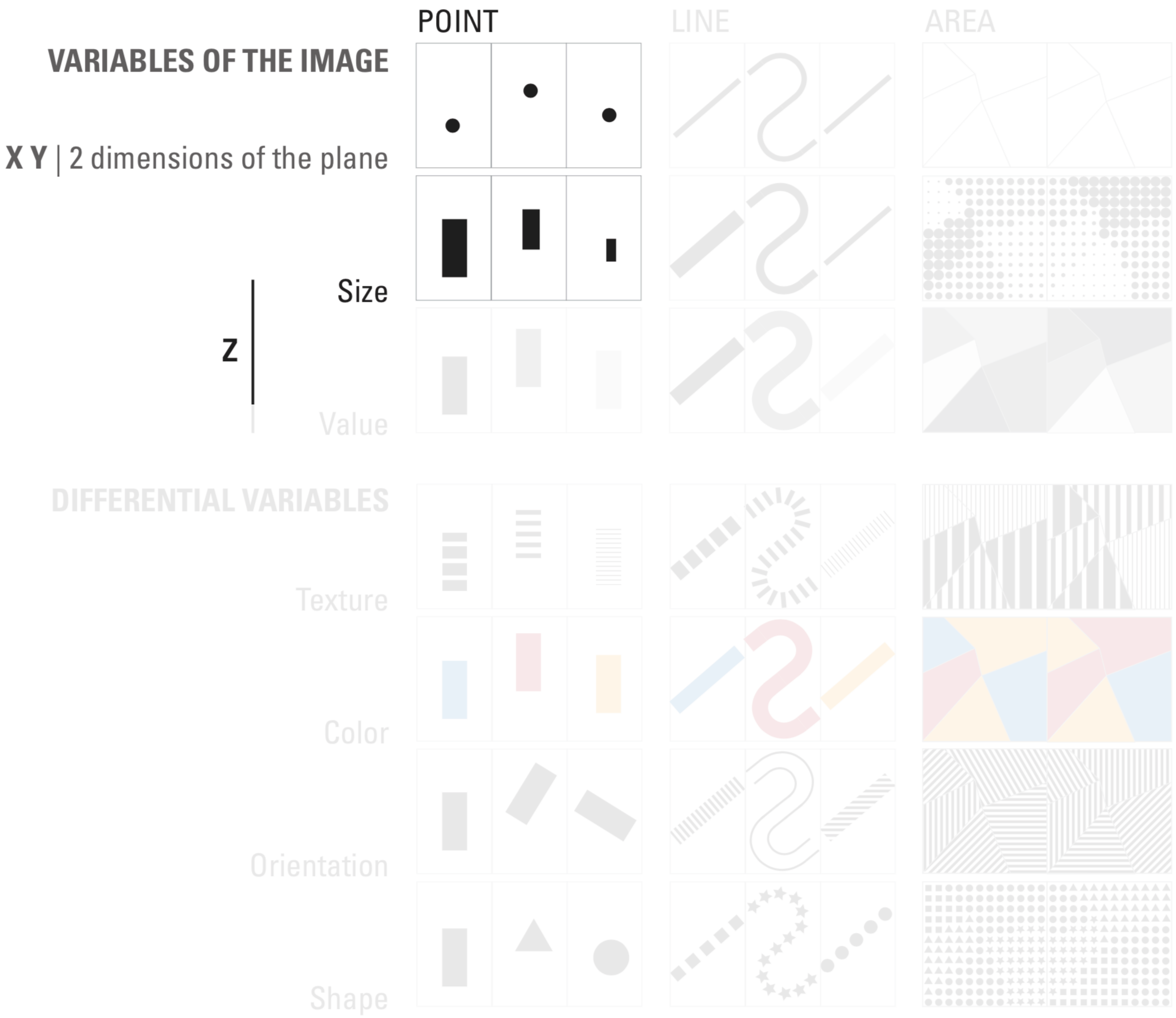
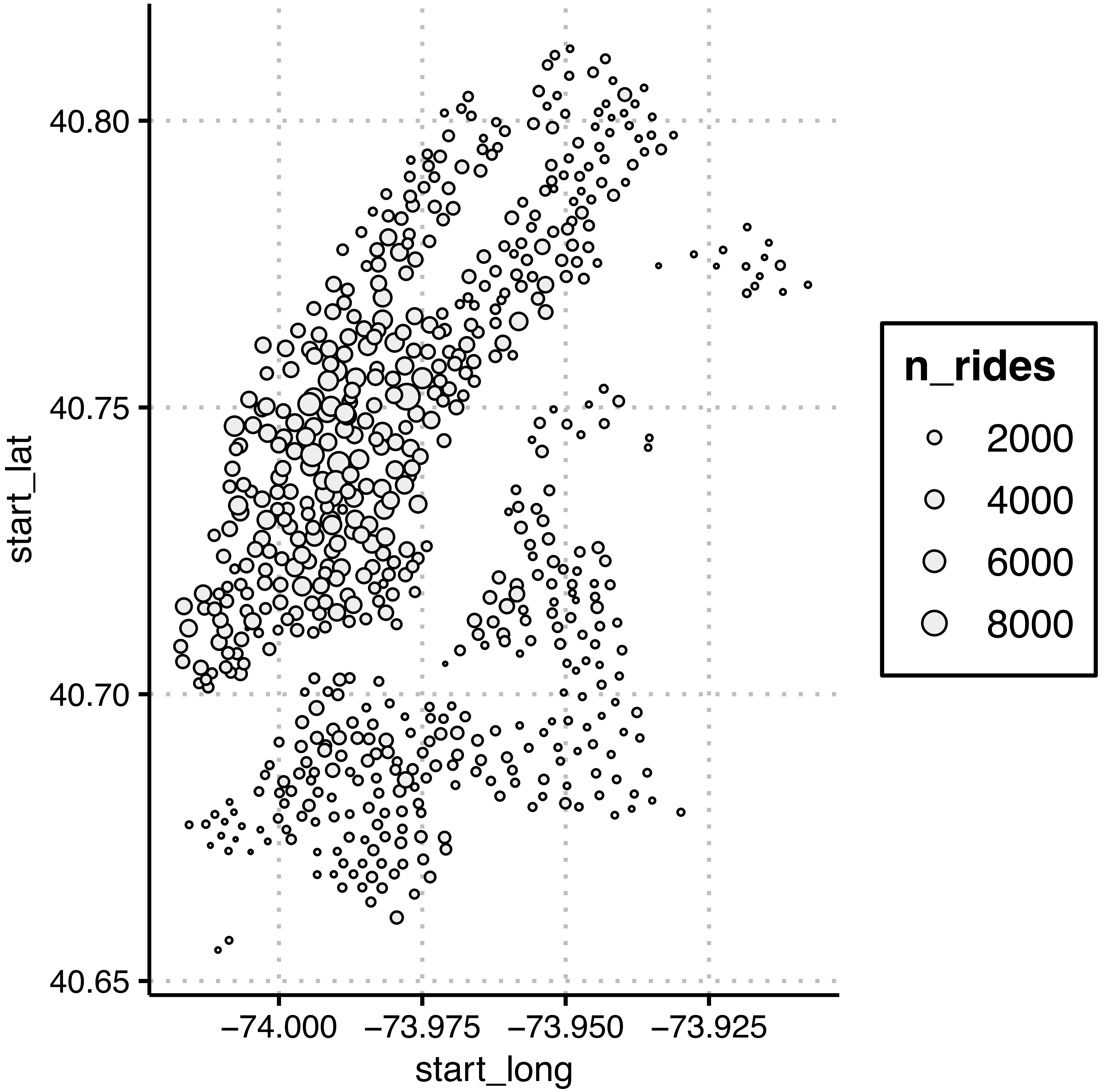
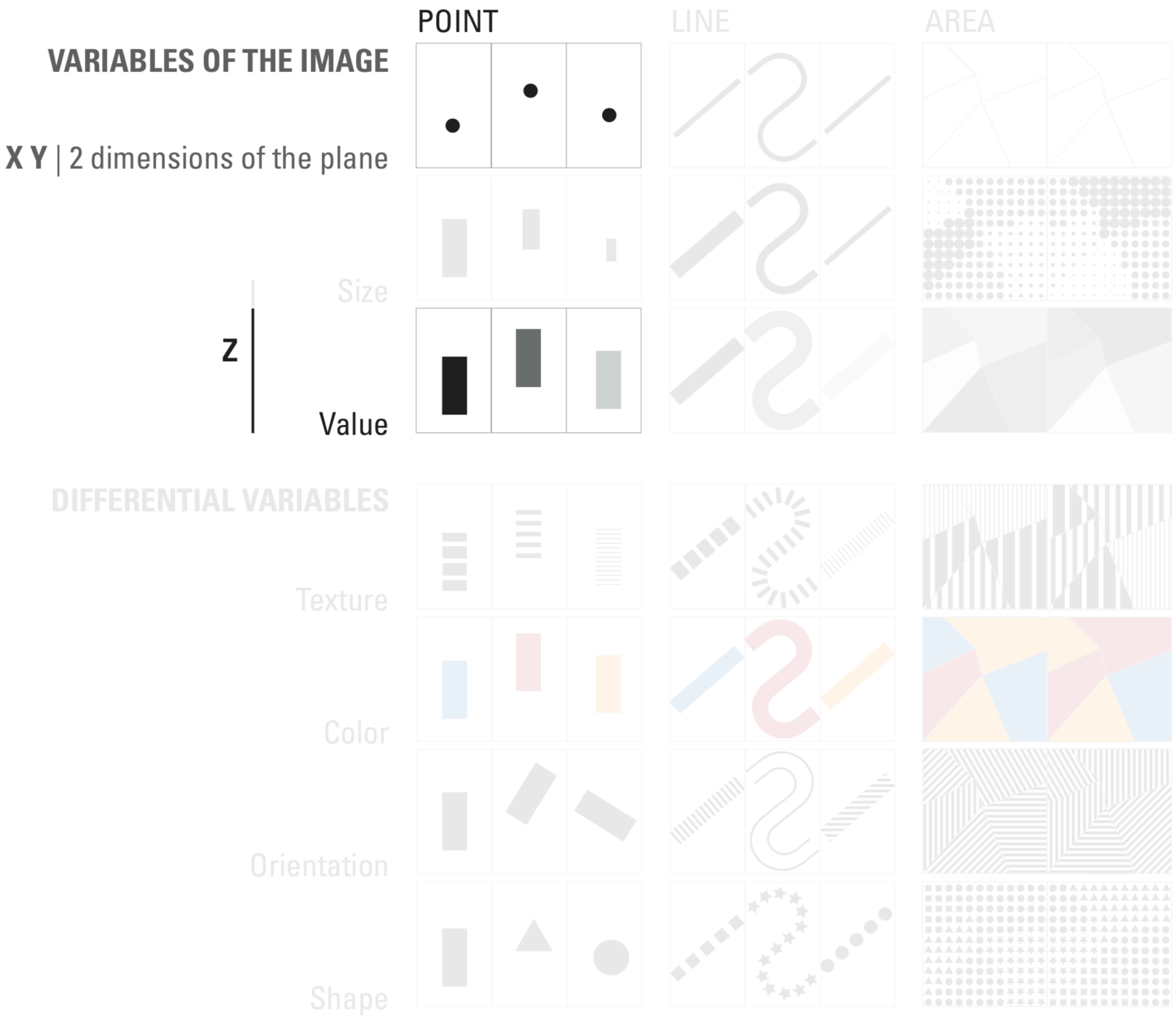


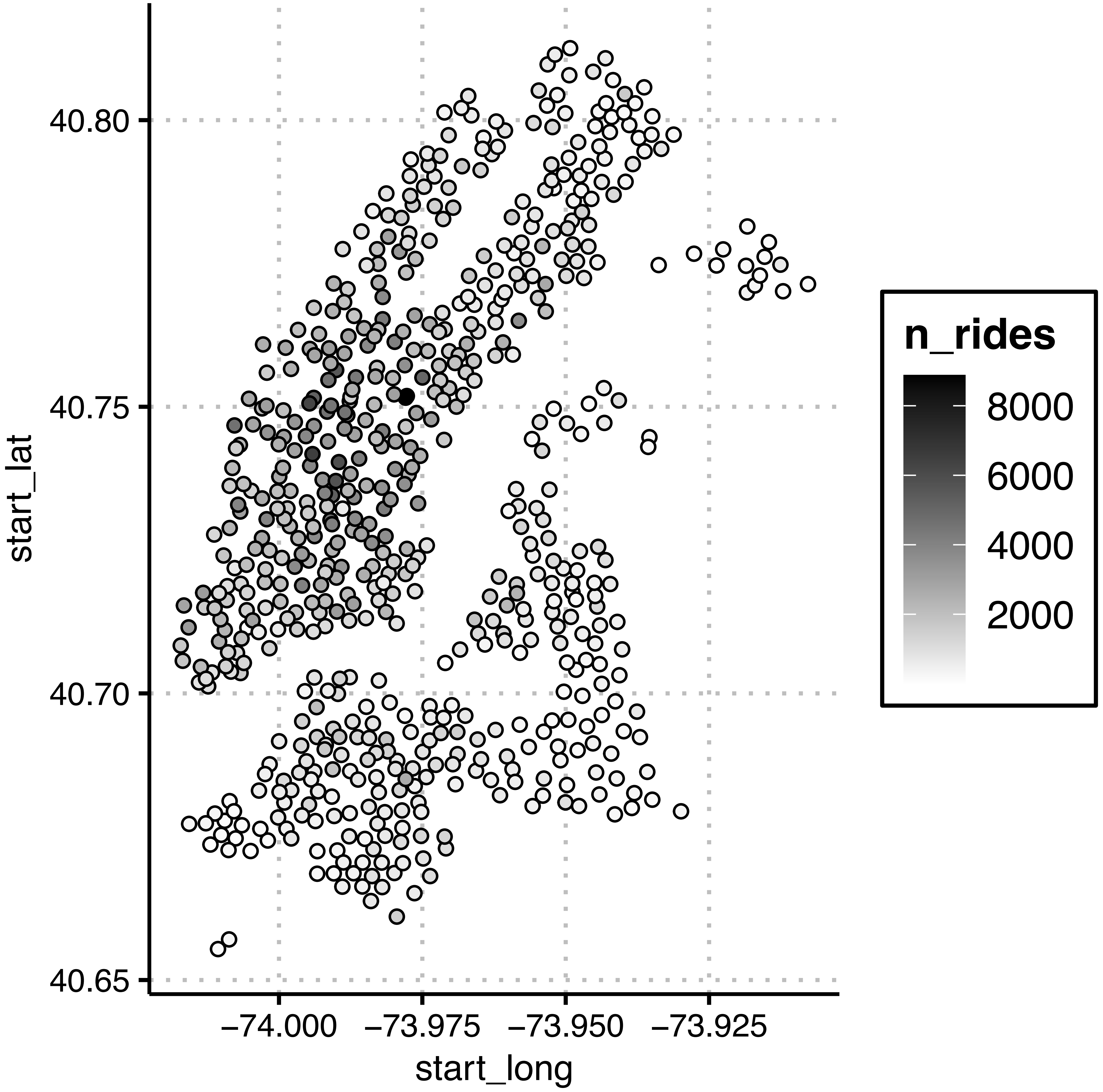


Citi Bike example — *exploratory data analysis*

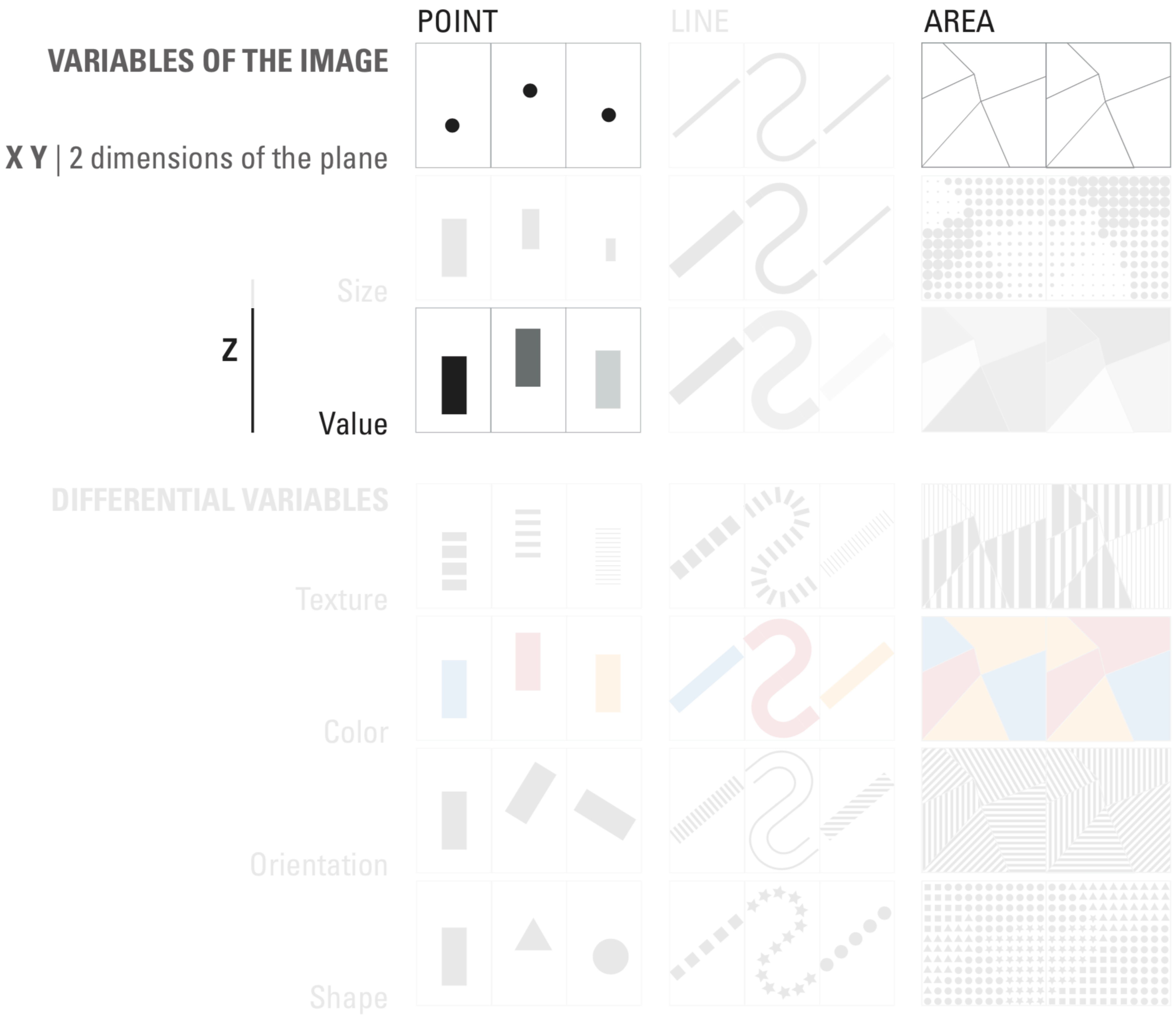


Citi Bike example — *exploratory data analysis*

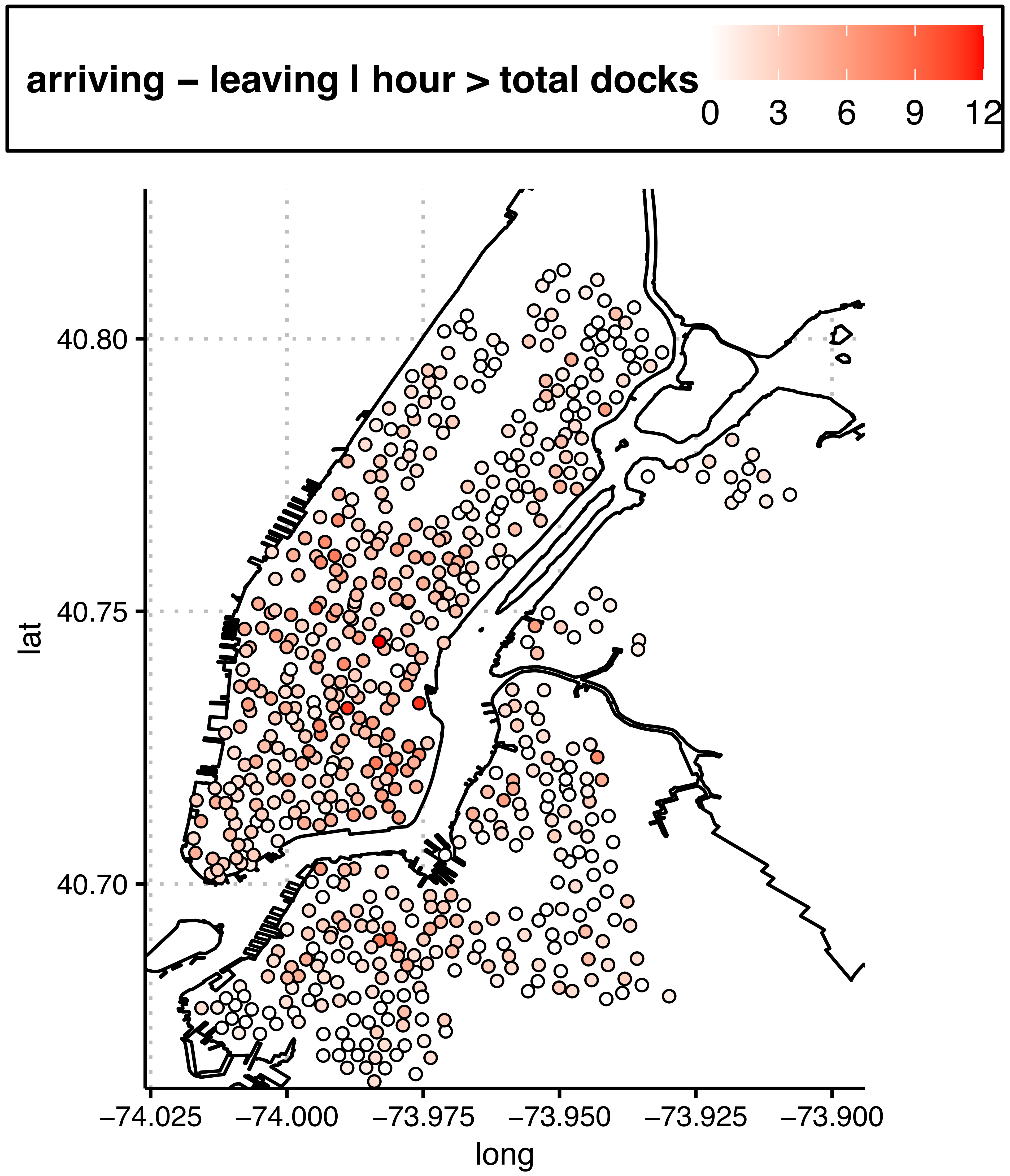




data encodings, visual channels for encoding data



Citi Bike example — *exploratory data analysis*



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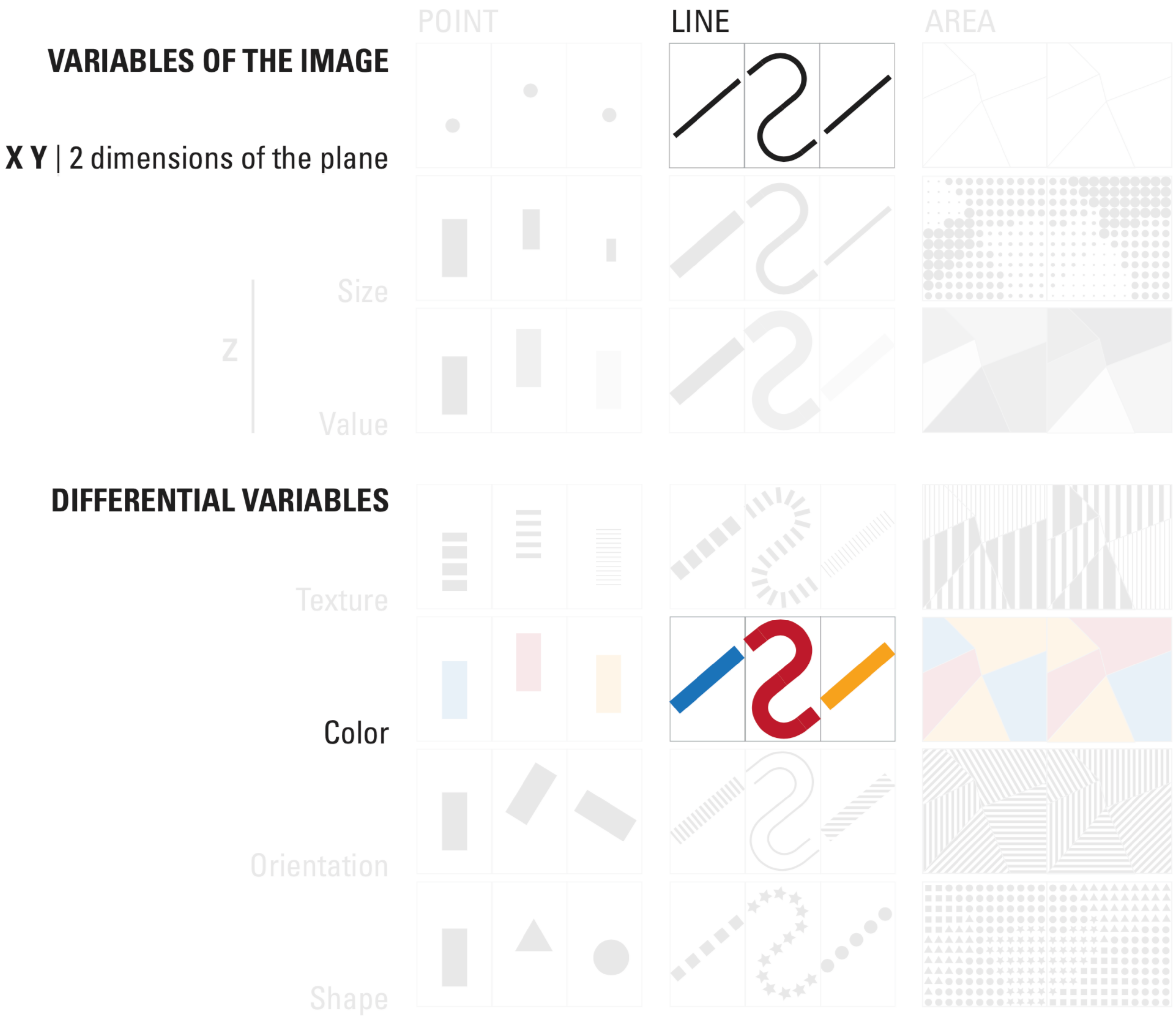

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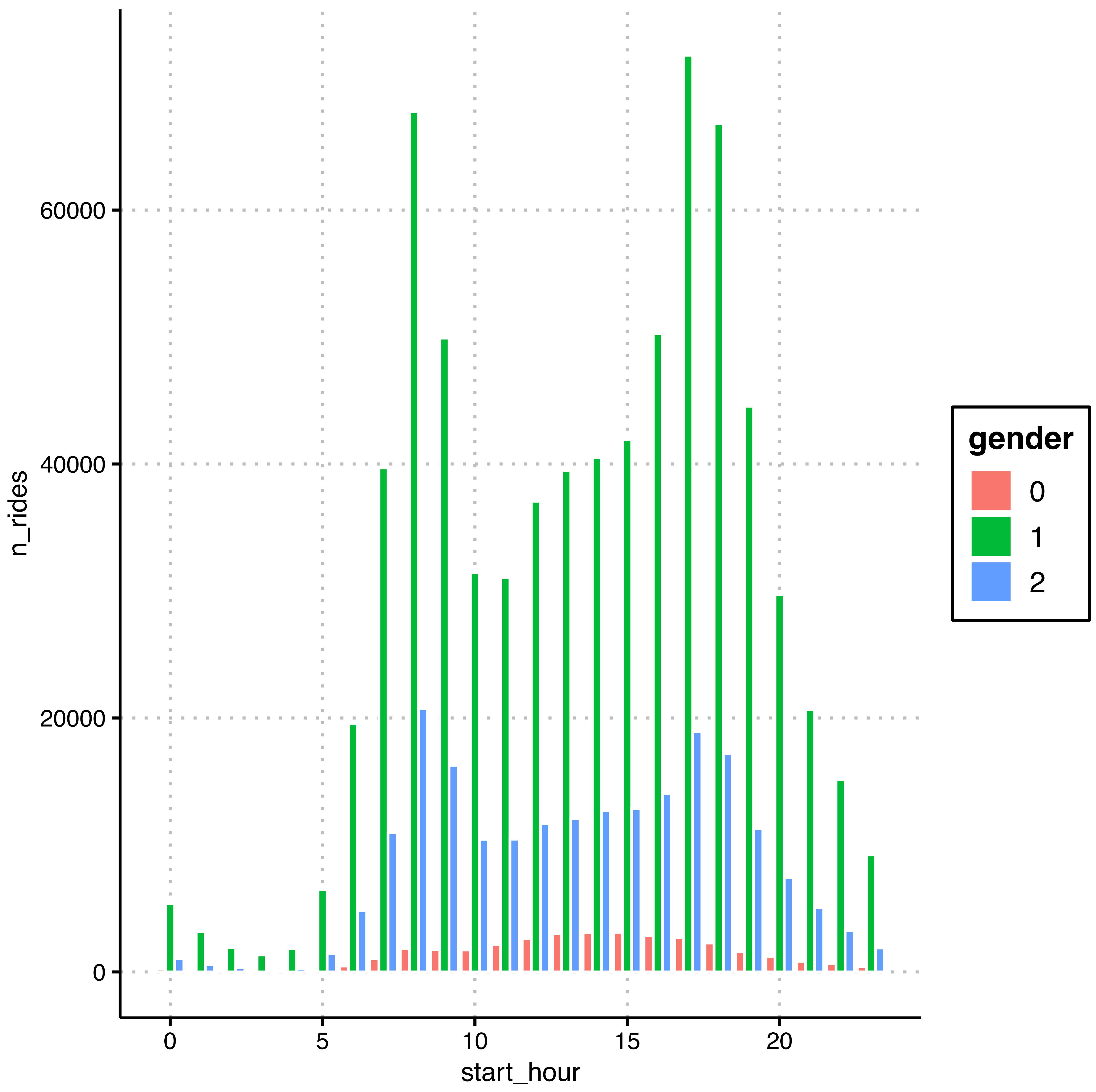
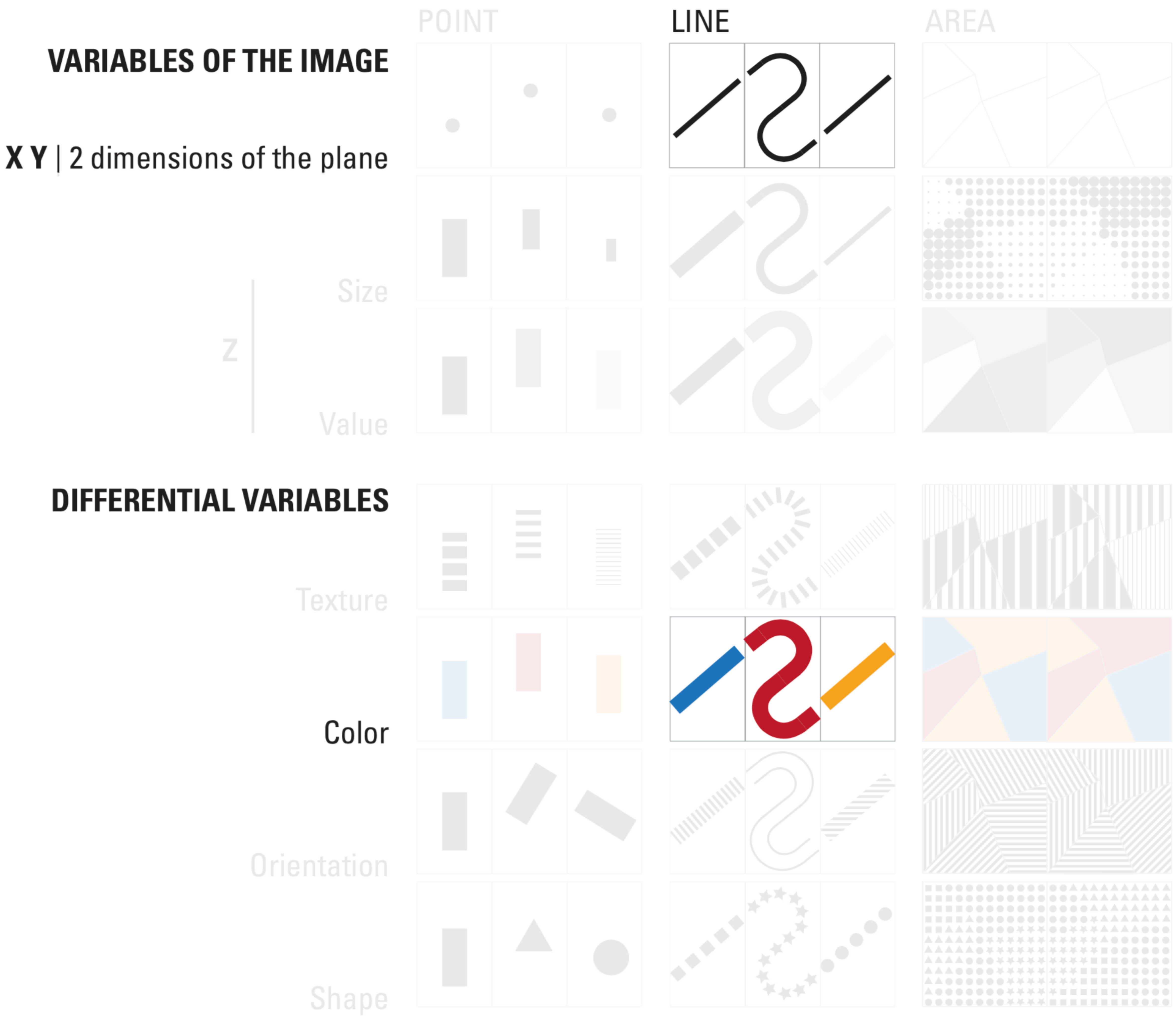
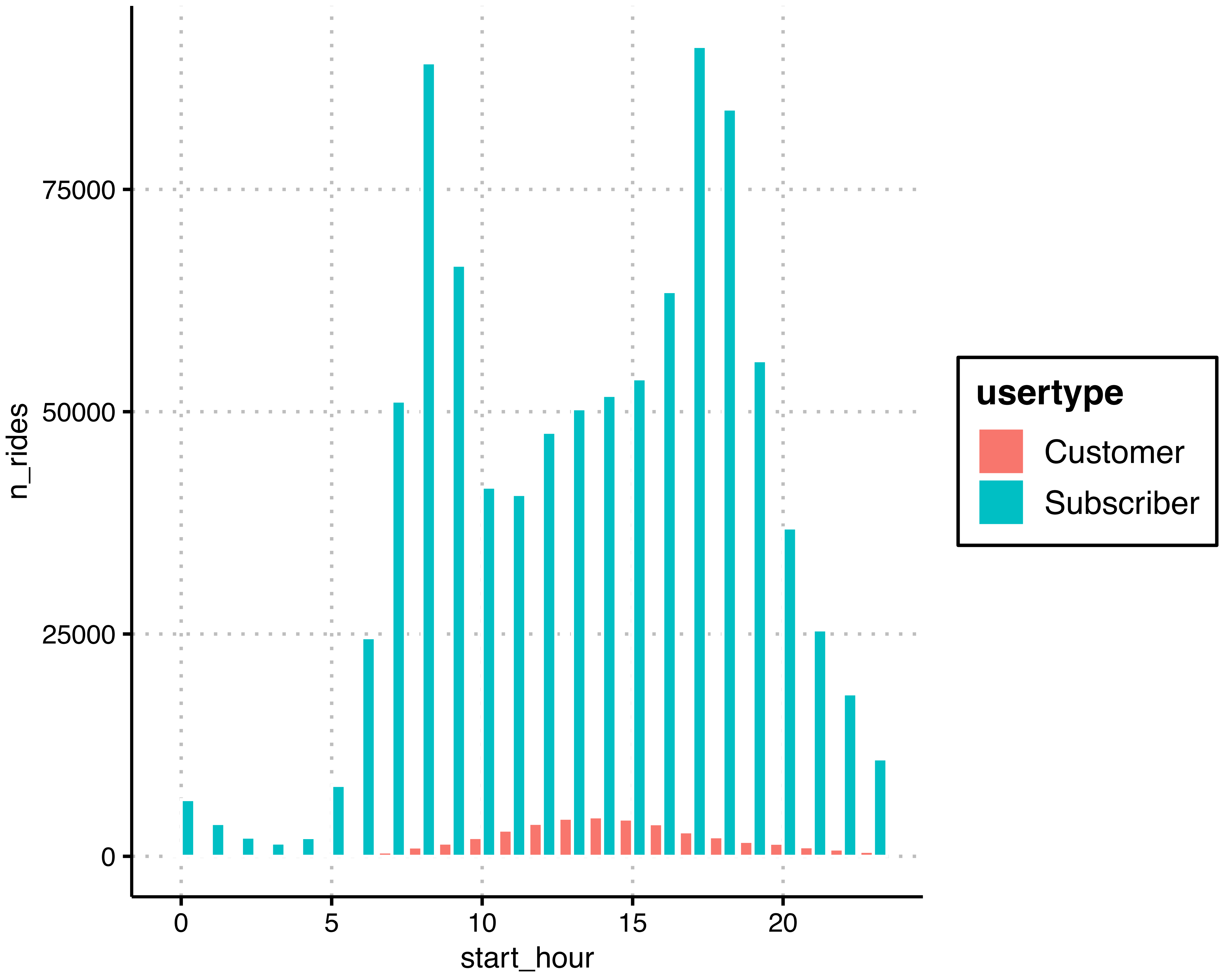


data encodings, **visual channels for encoding data**

Citi Bike example — *exploratory data analysis*





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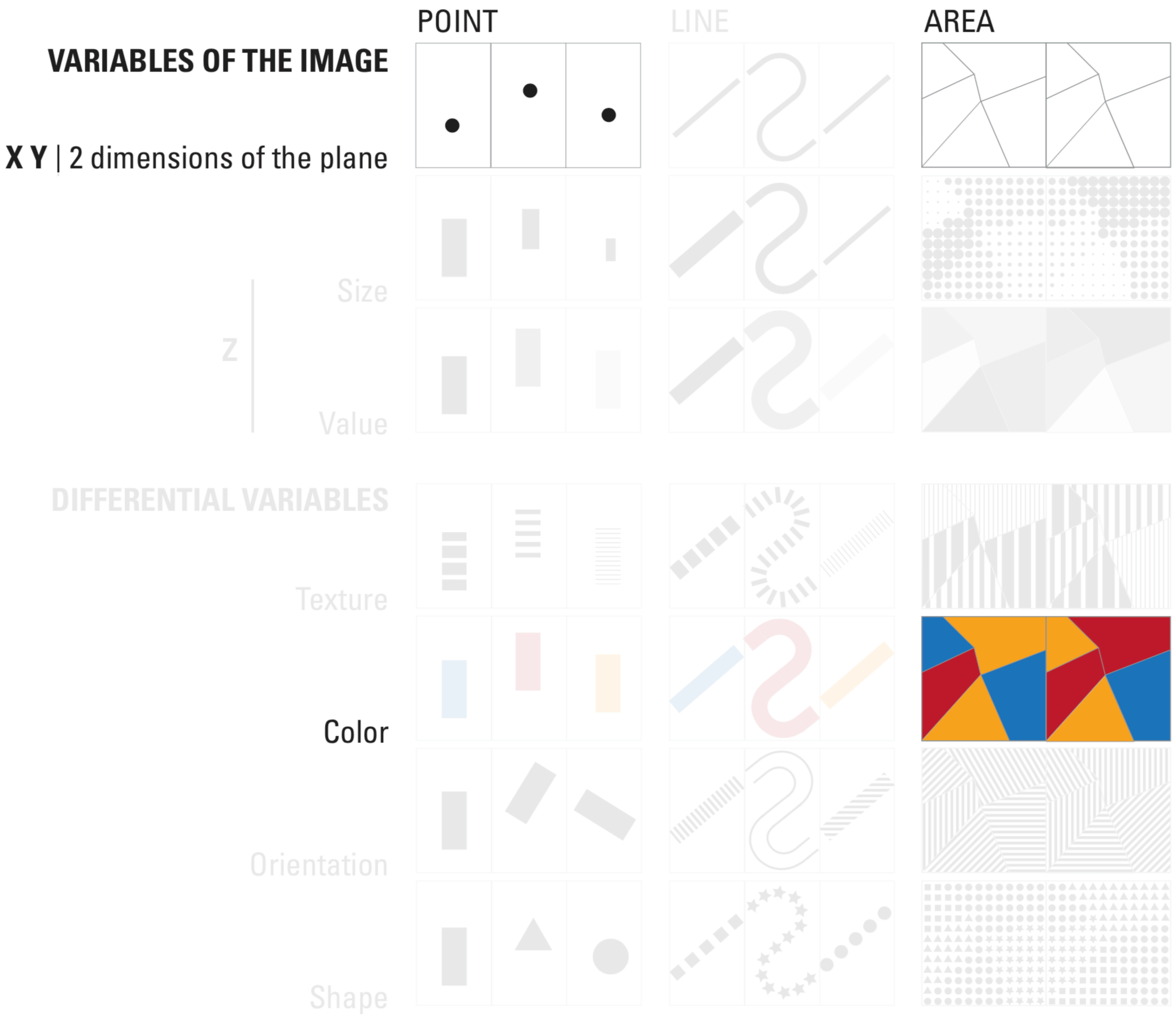

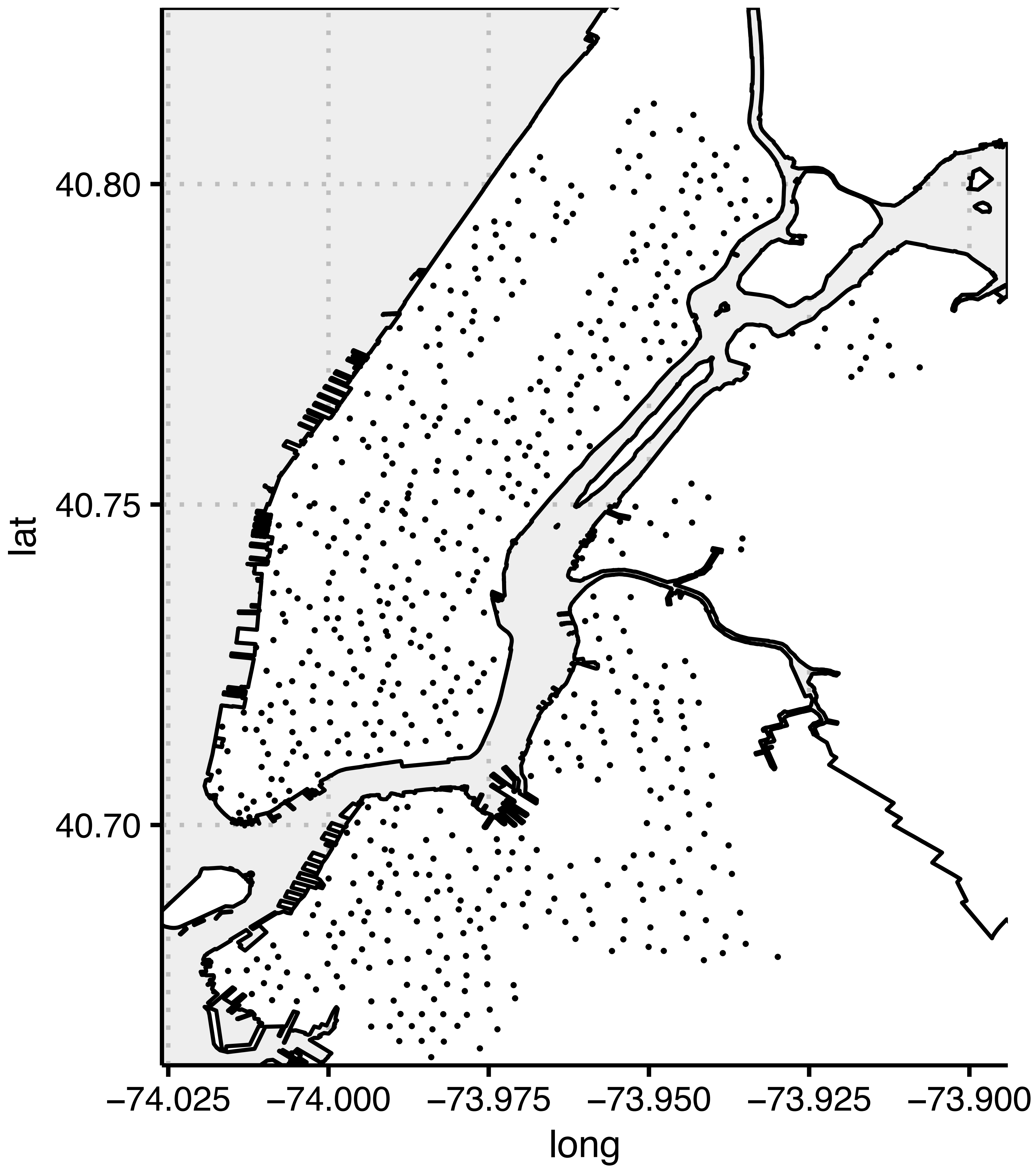

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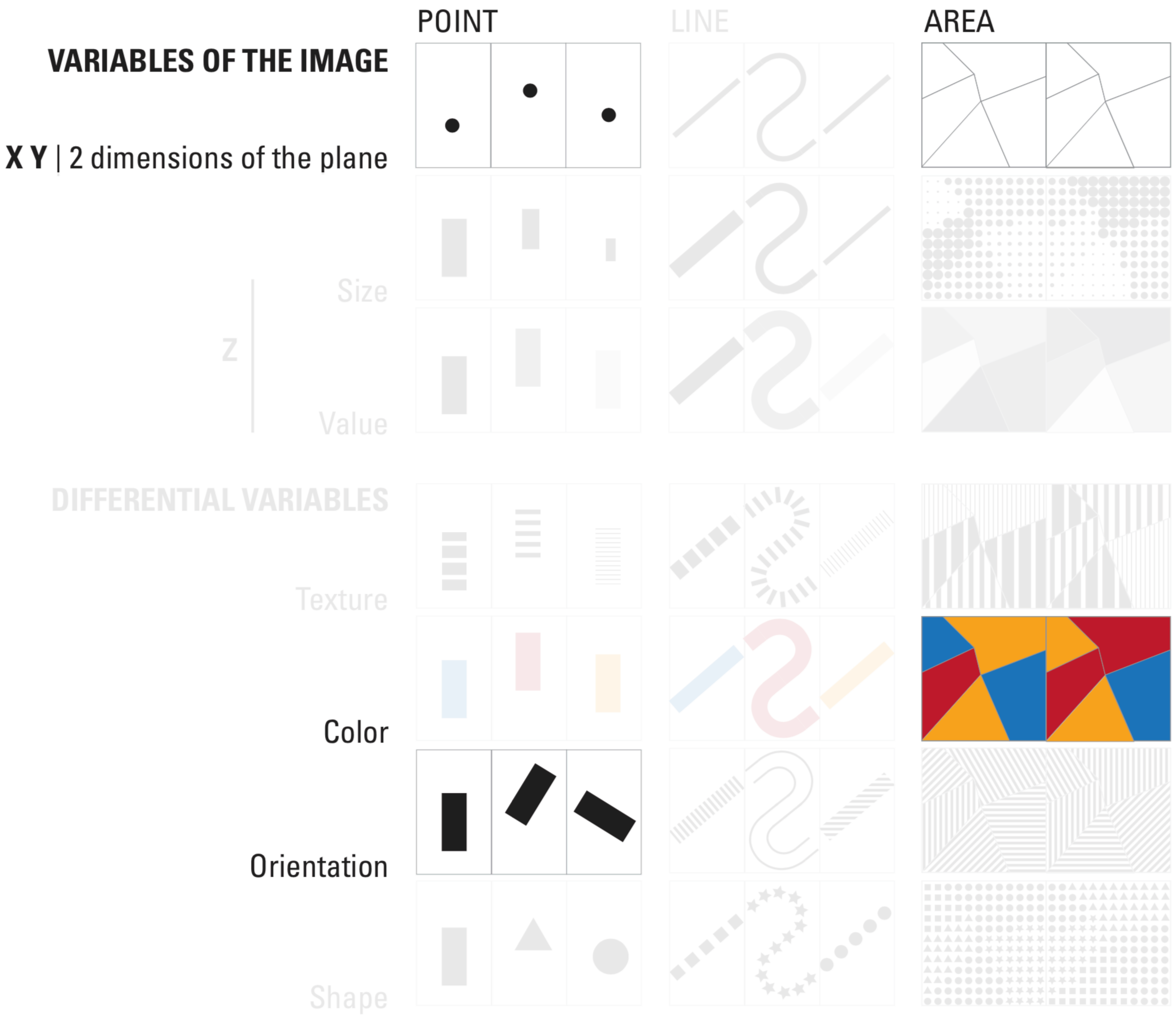

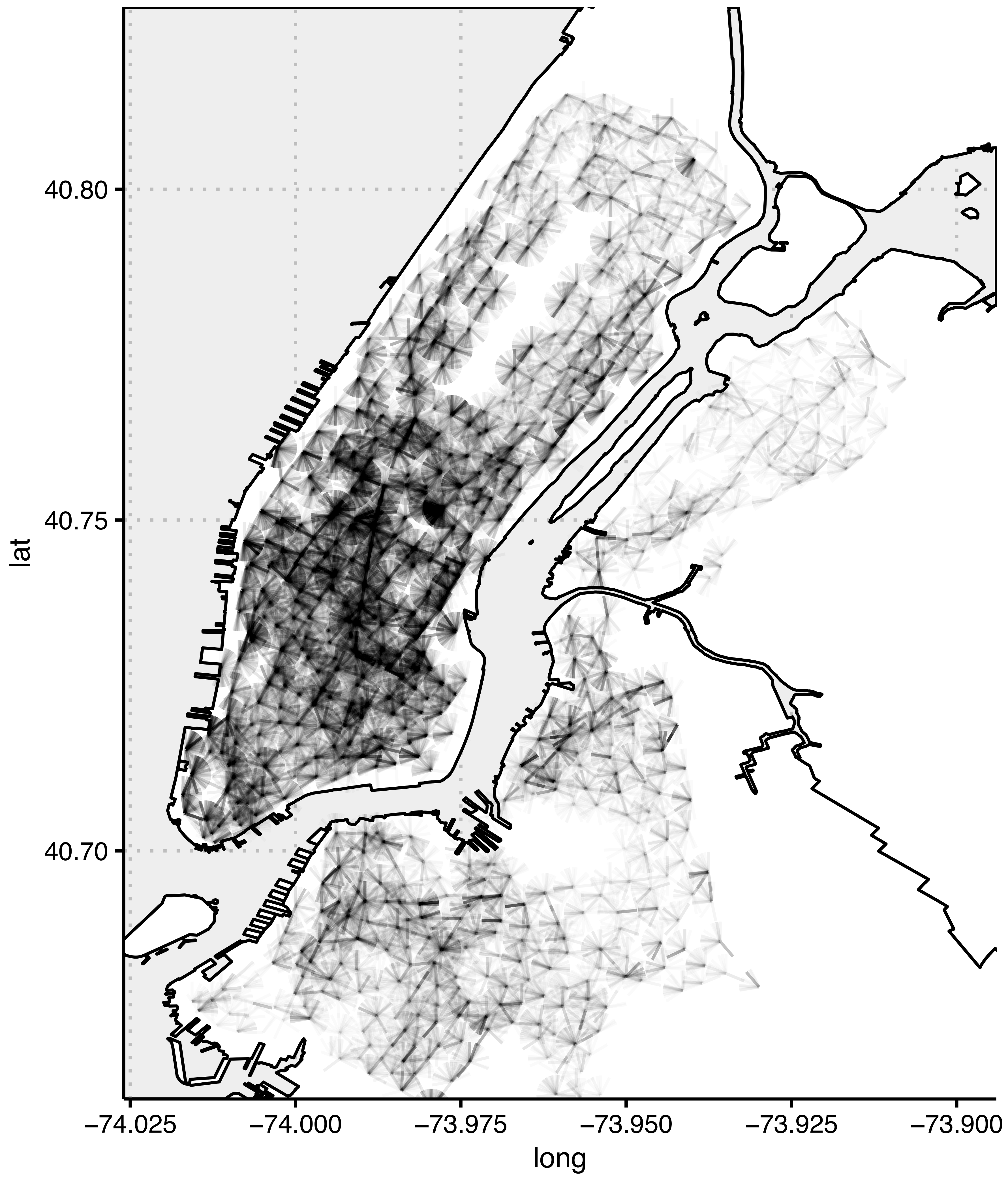

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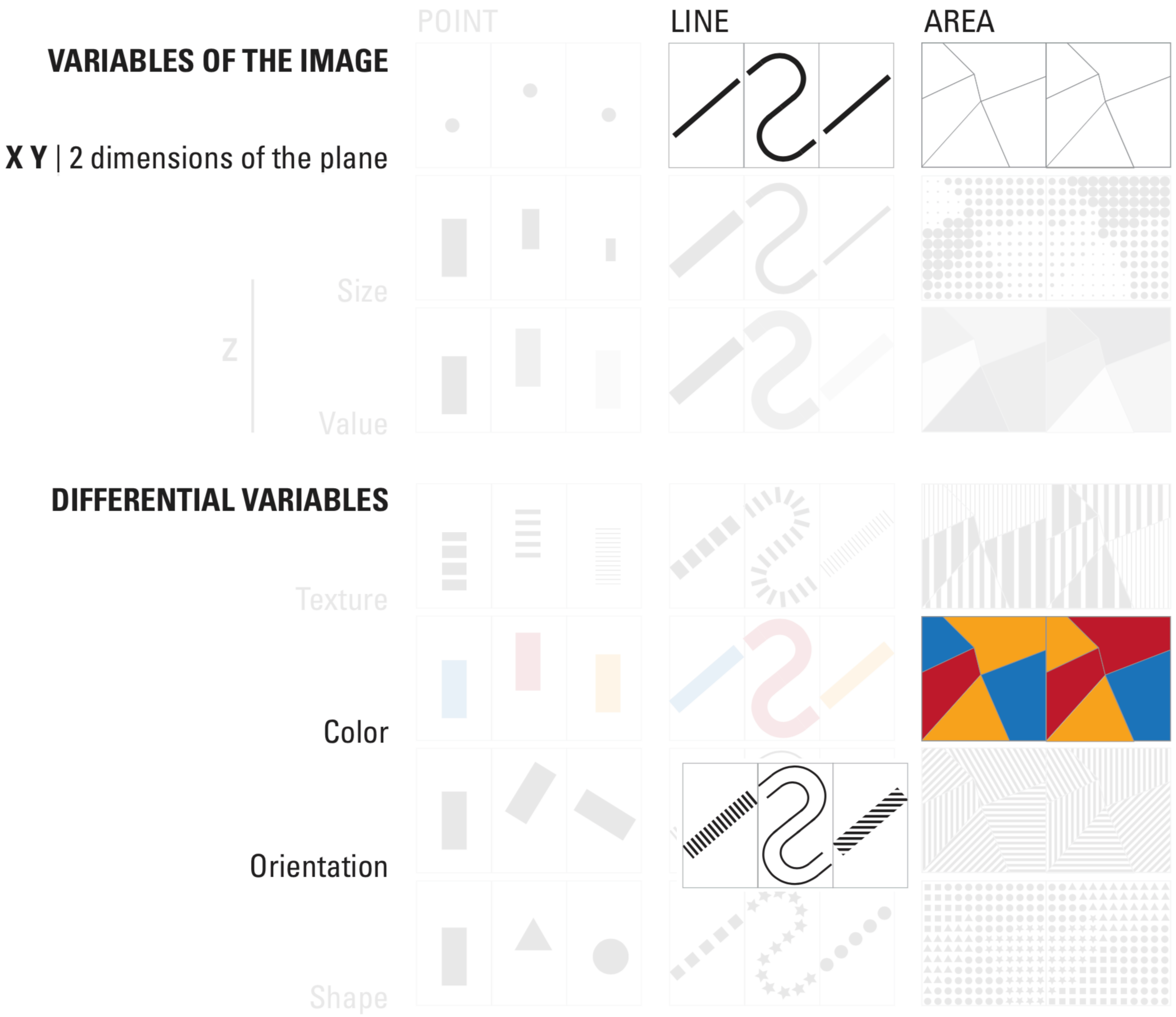
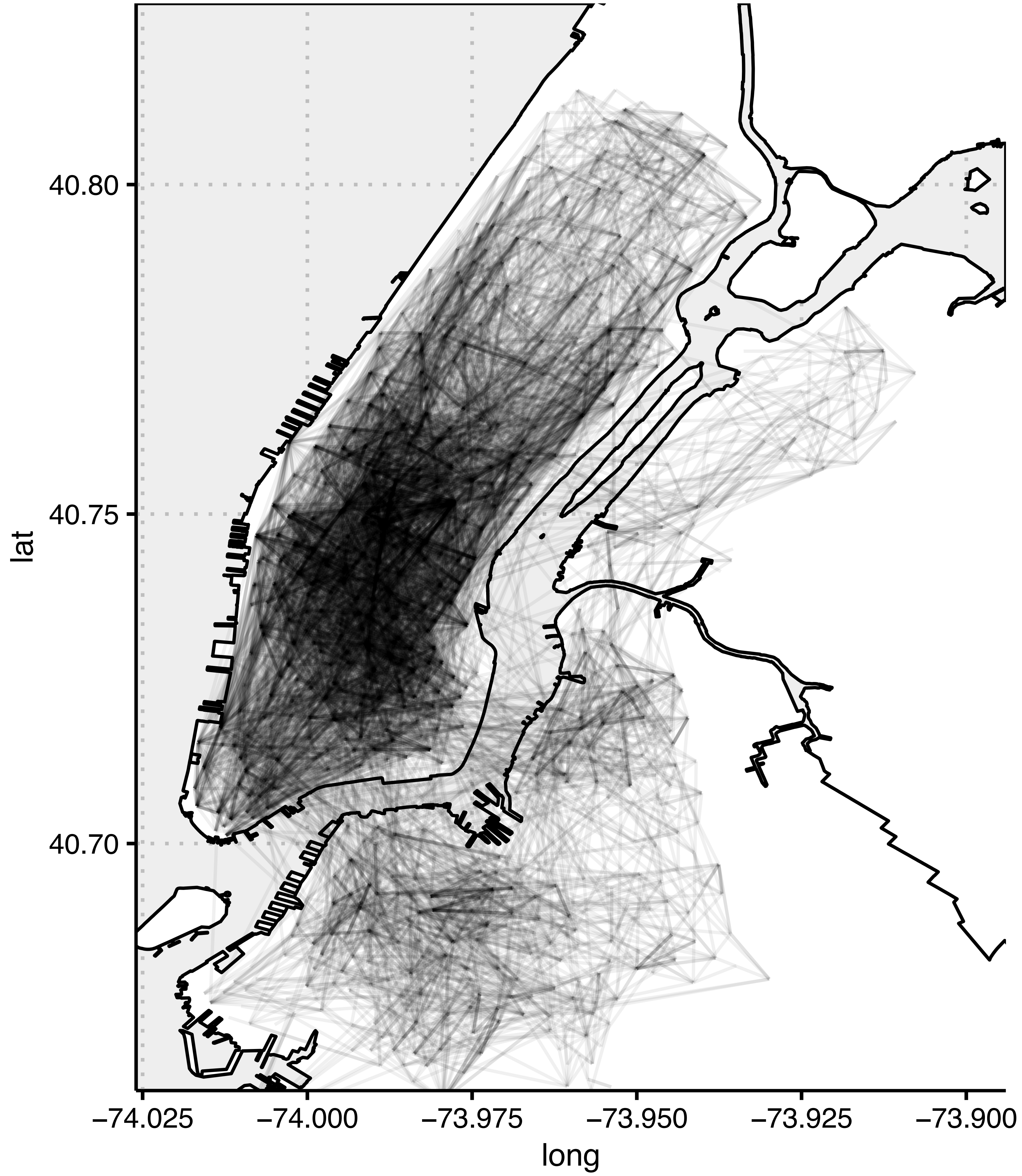
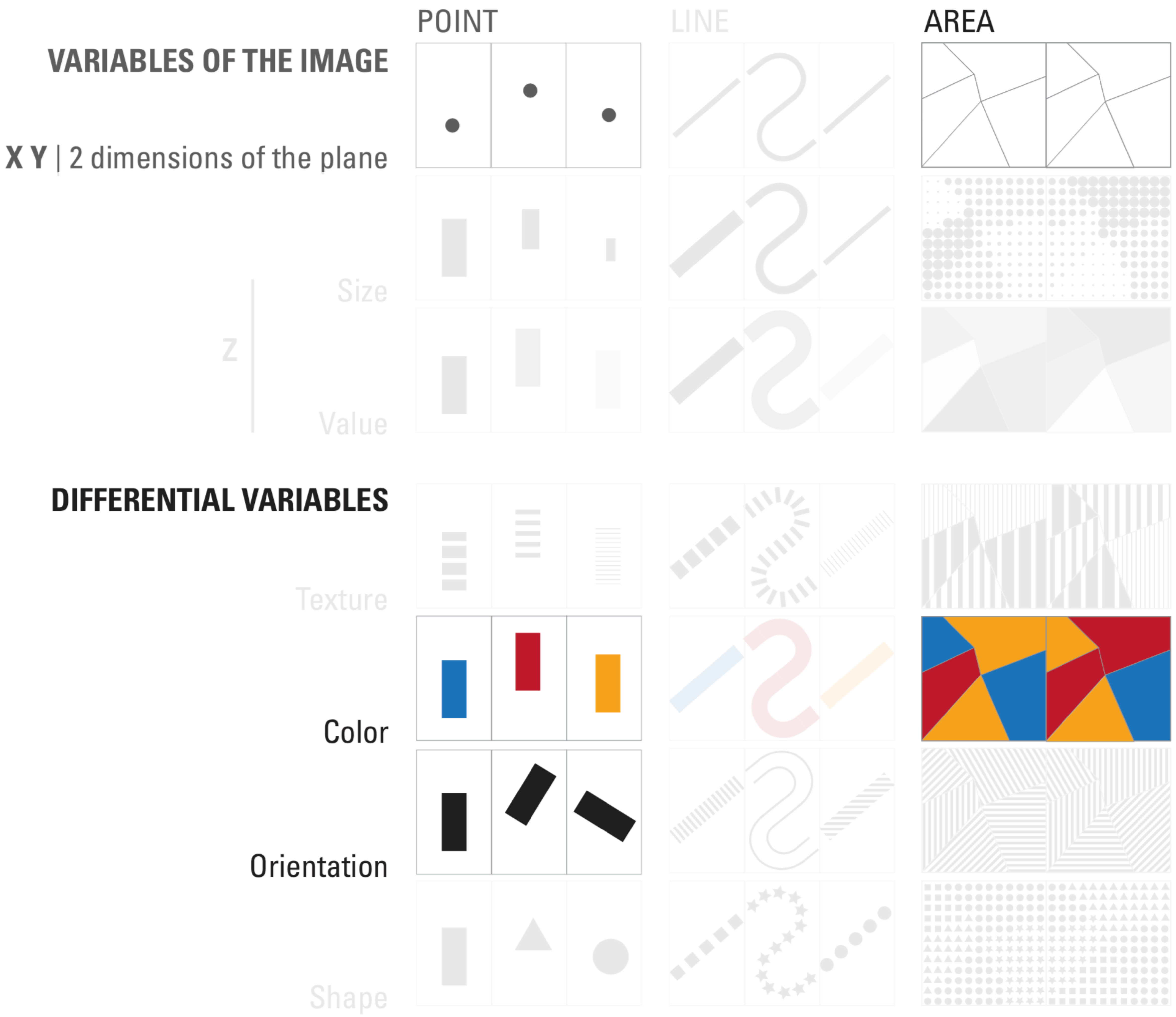




data encodings, **visual channels for encoding data**



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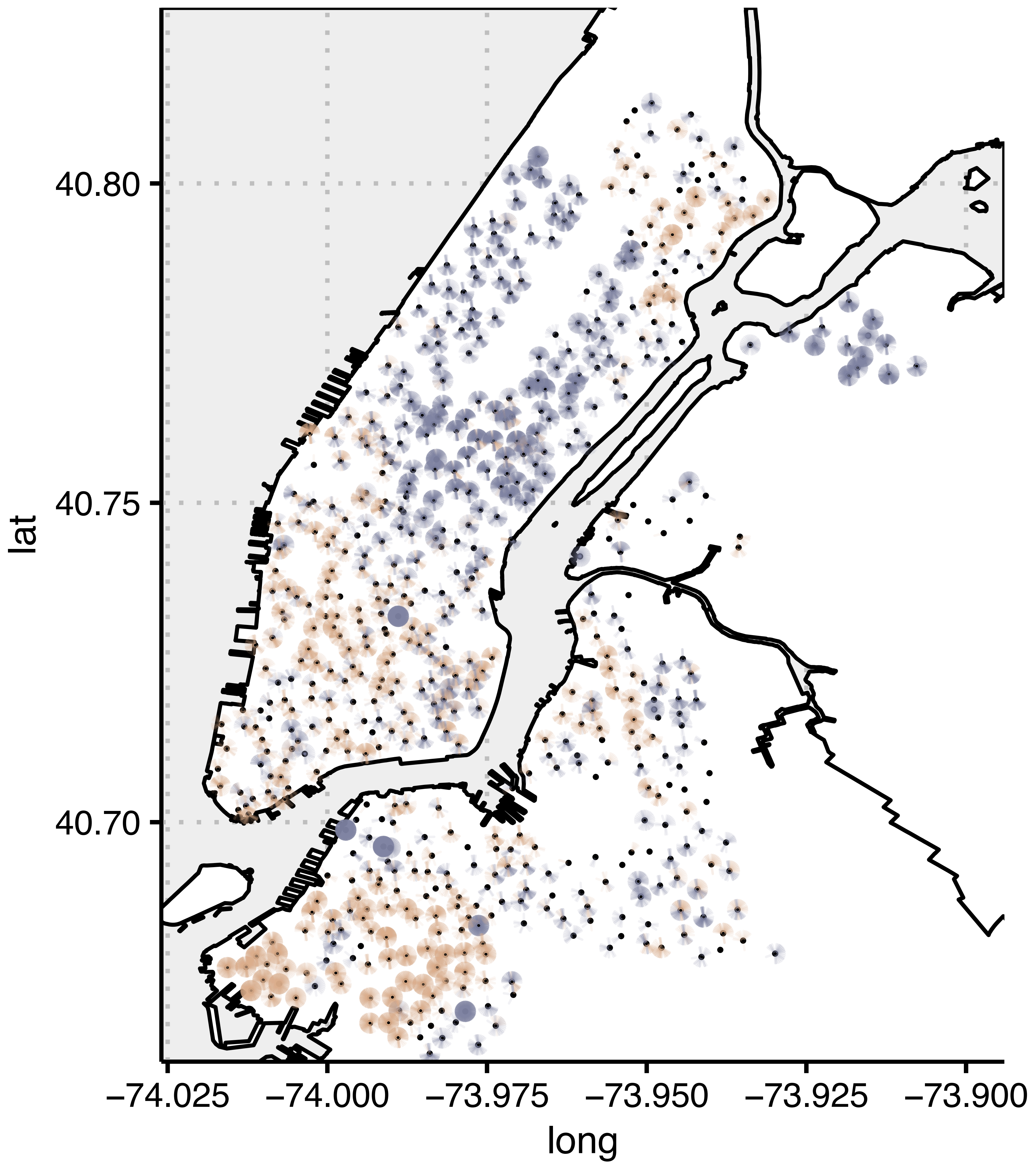

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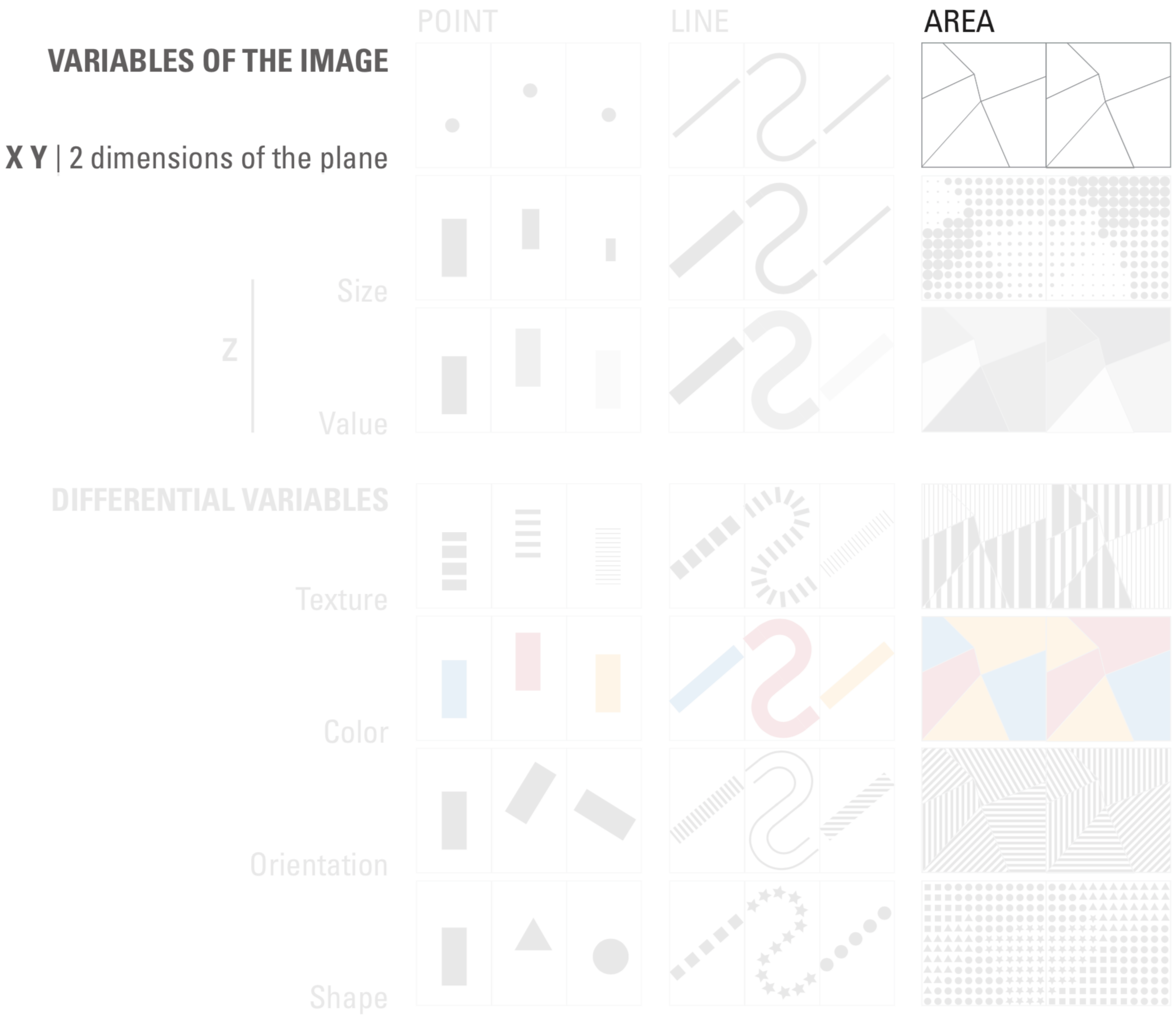
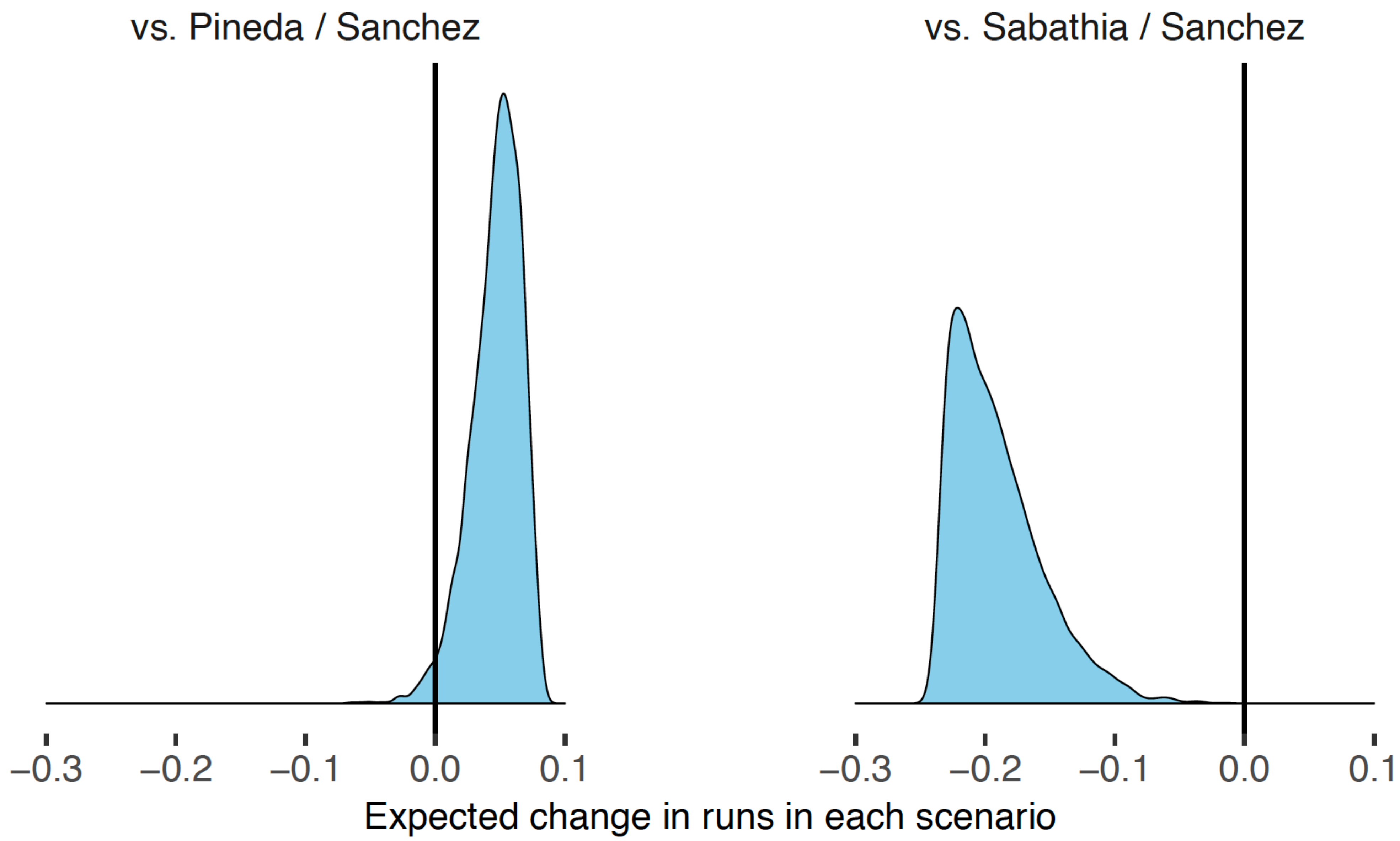
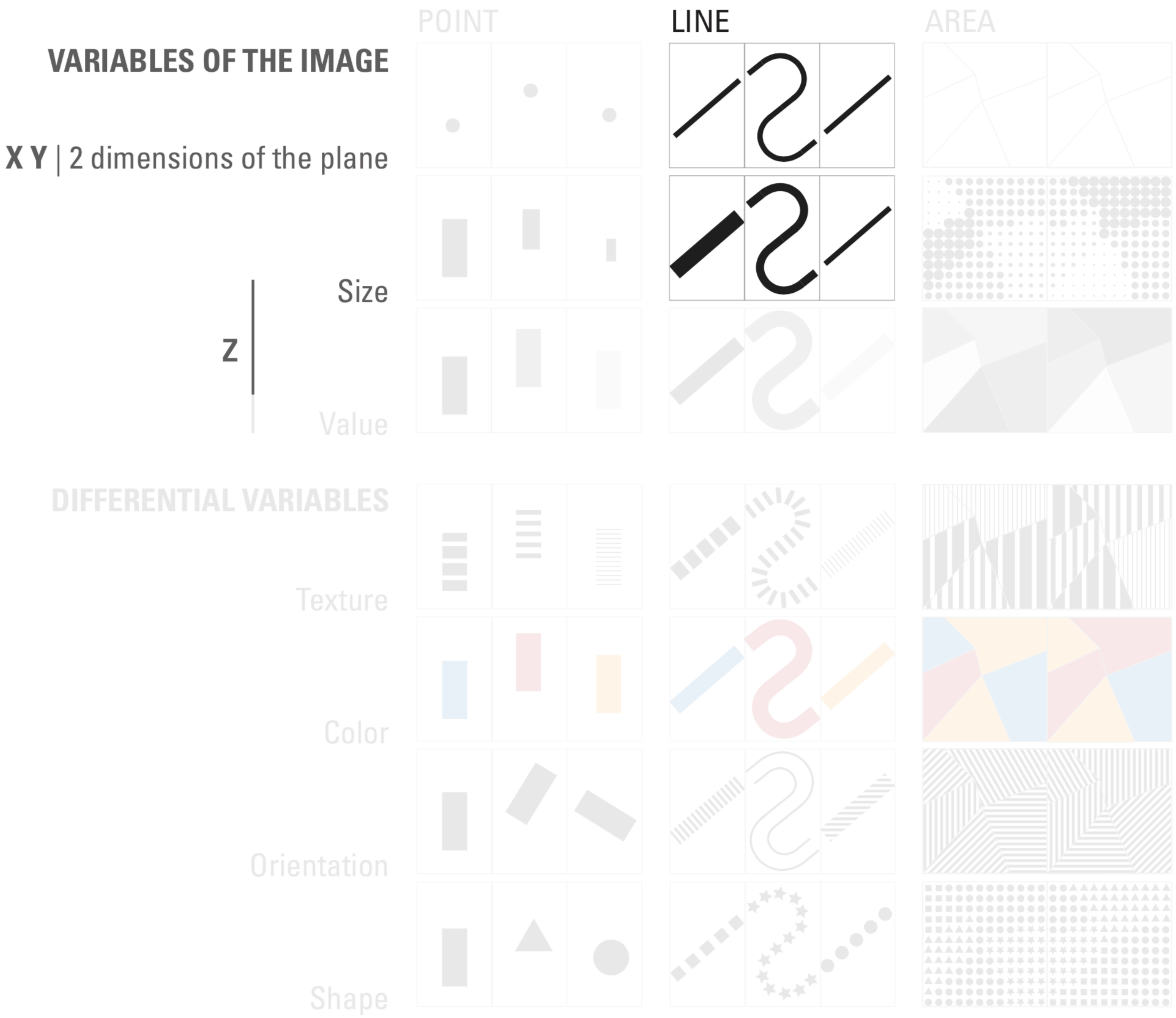
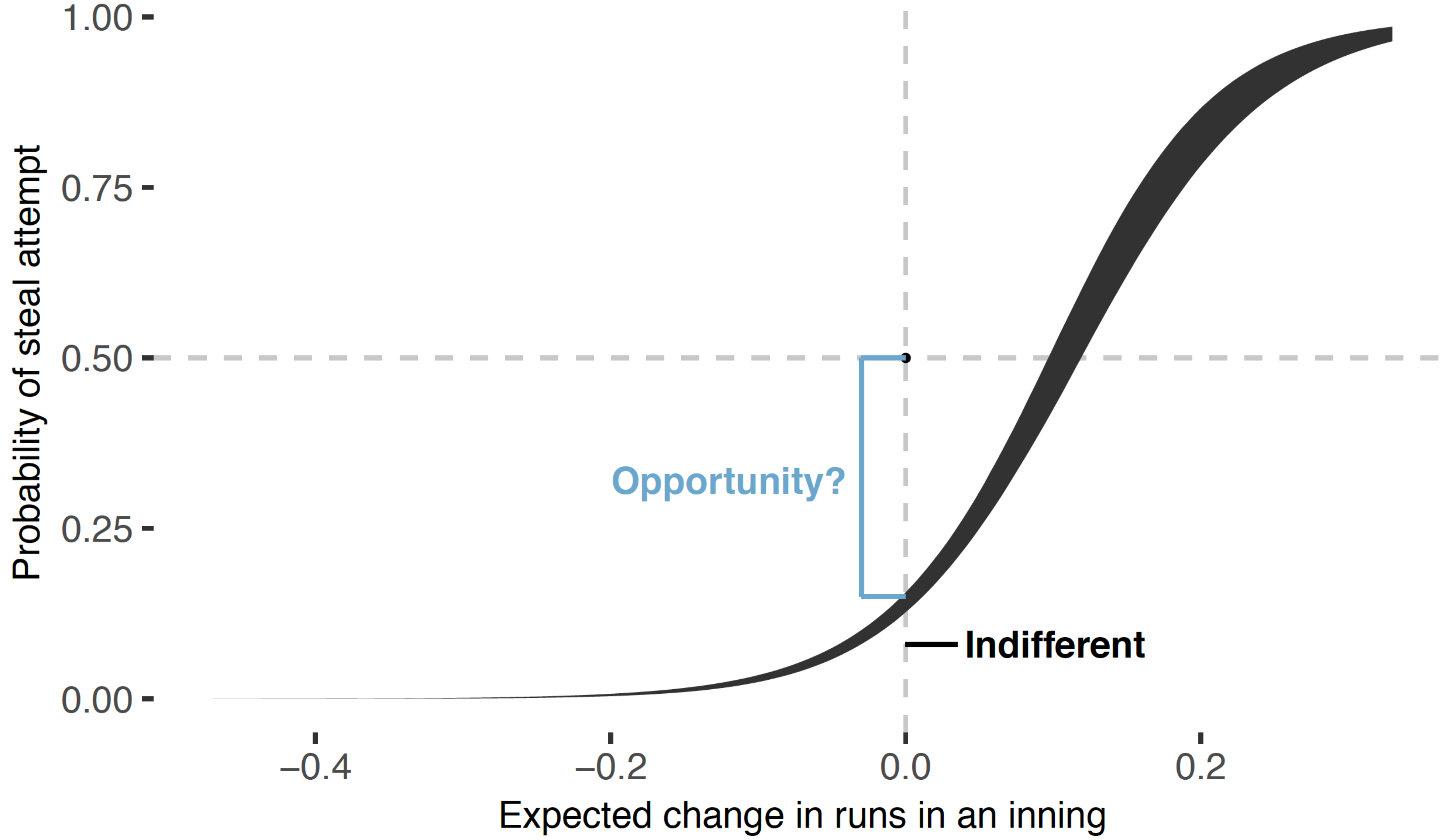


Dodgers *draft* proposal example





Dodgers *draft* proposal example

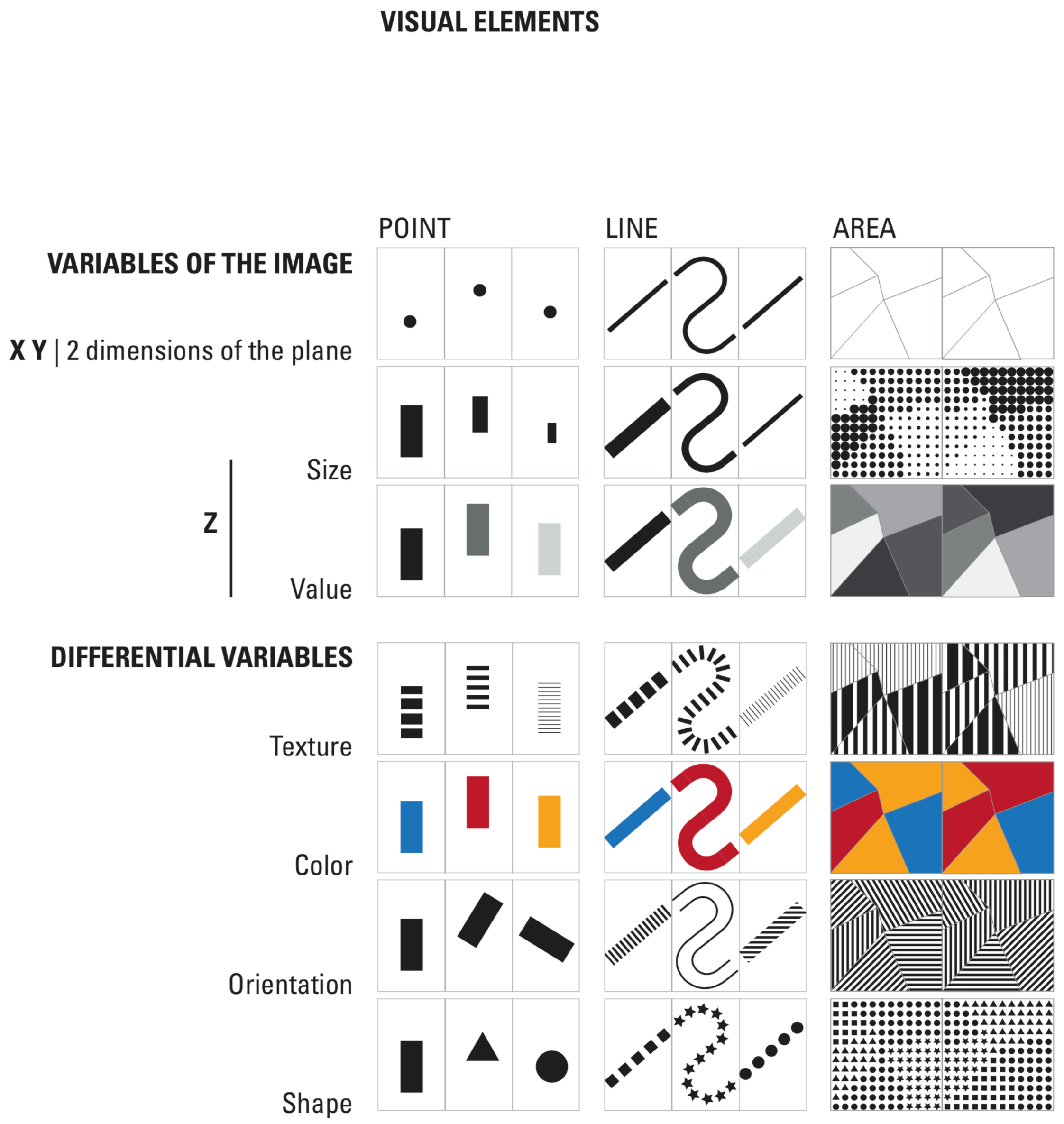


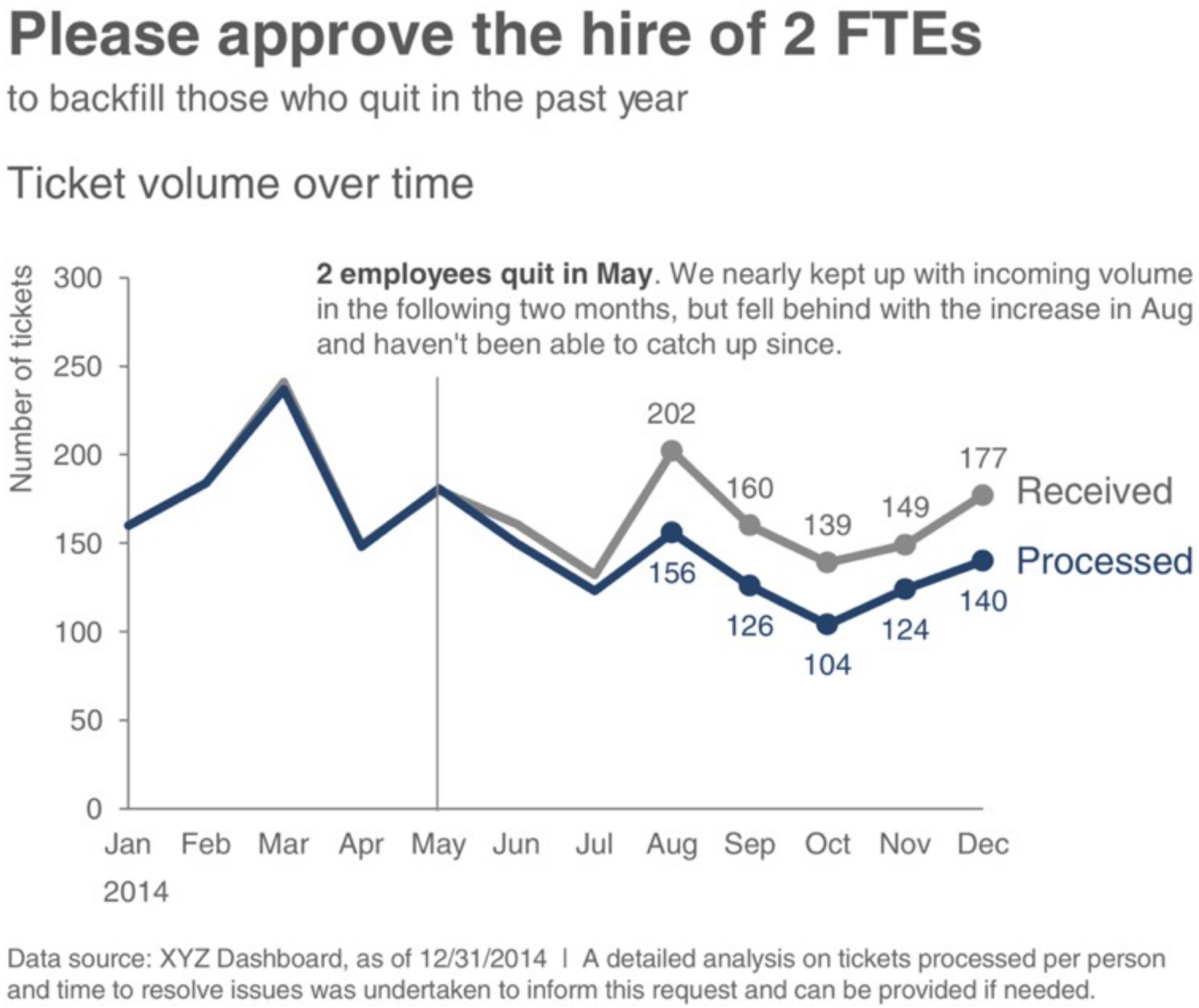
adding dimensions through small multiples

data encodings, small multiples (of area + color + point + value) Citi Bike example — *exploratory data analysis*

class exercises

exercise, identify data encodings in visual channels





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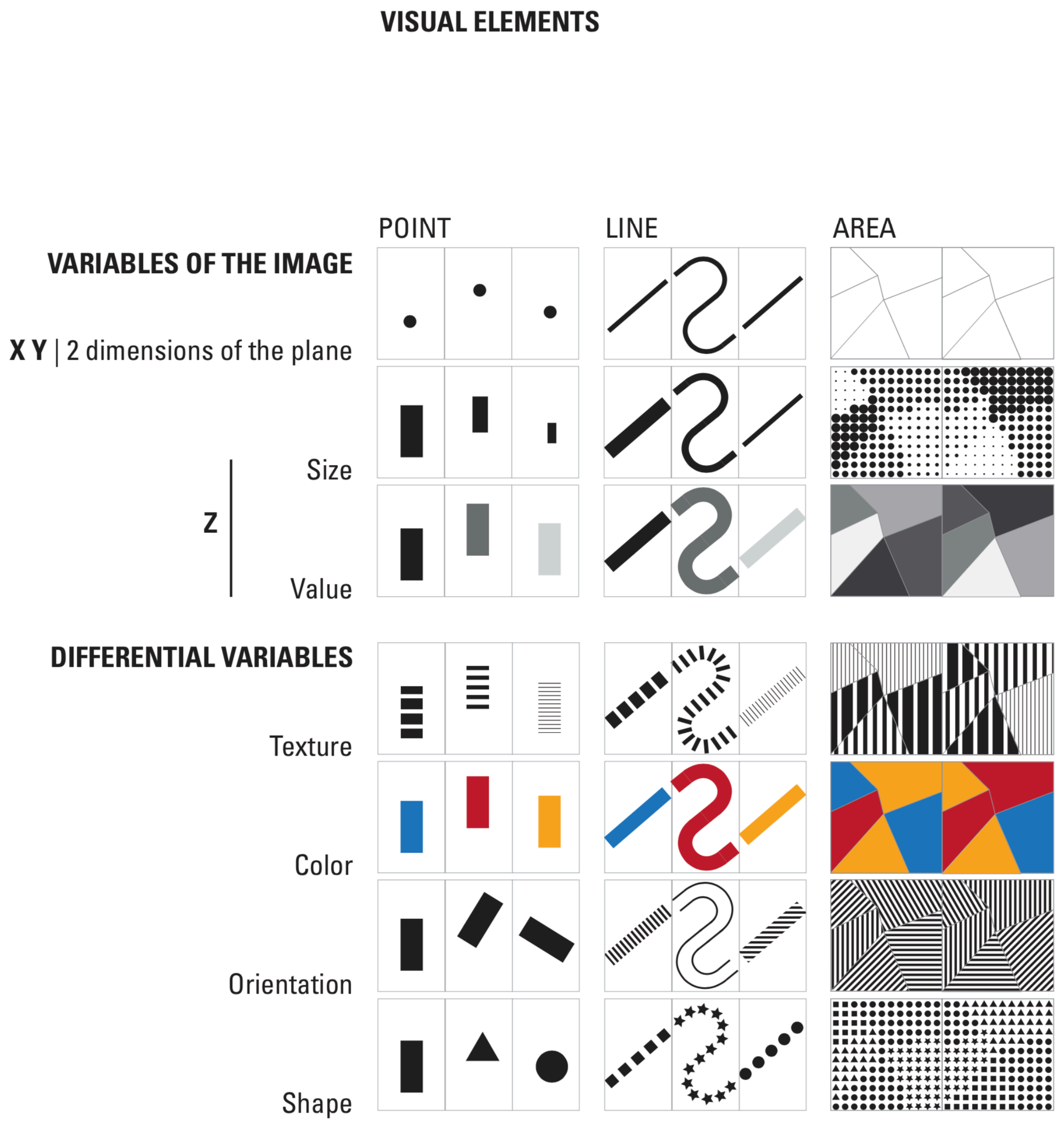
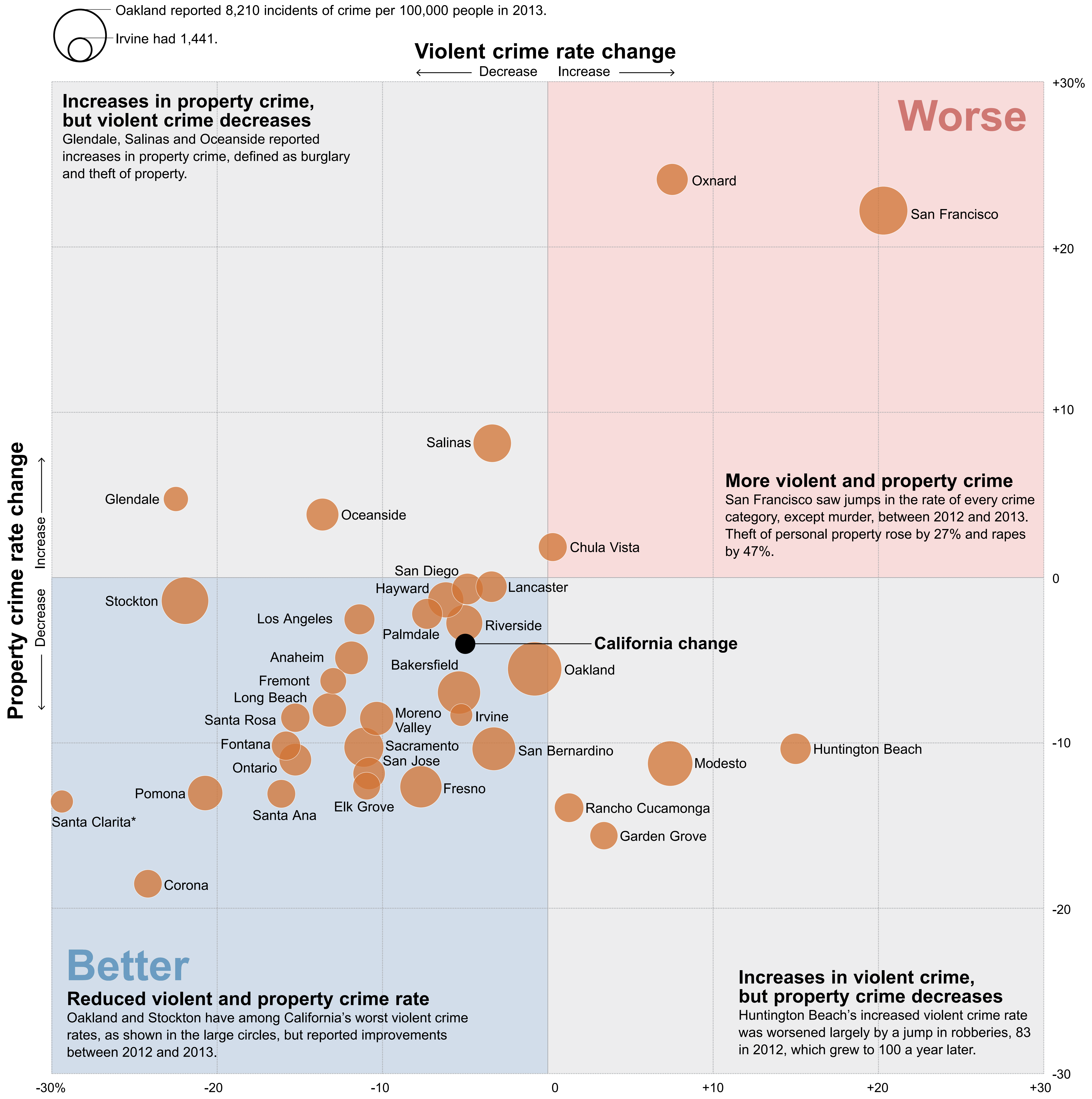
exercise, identify data encodings in visual channels





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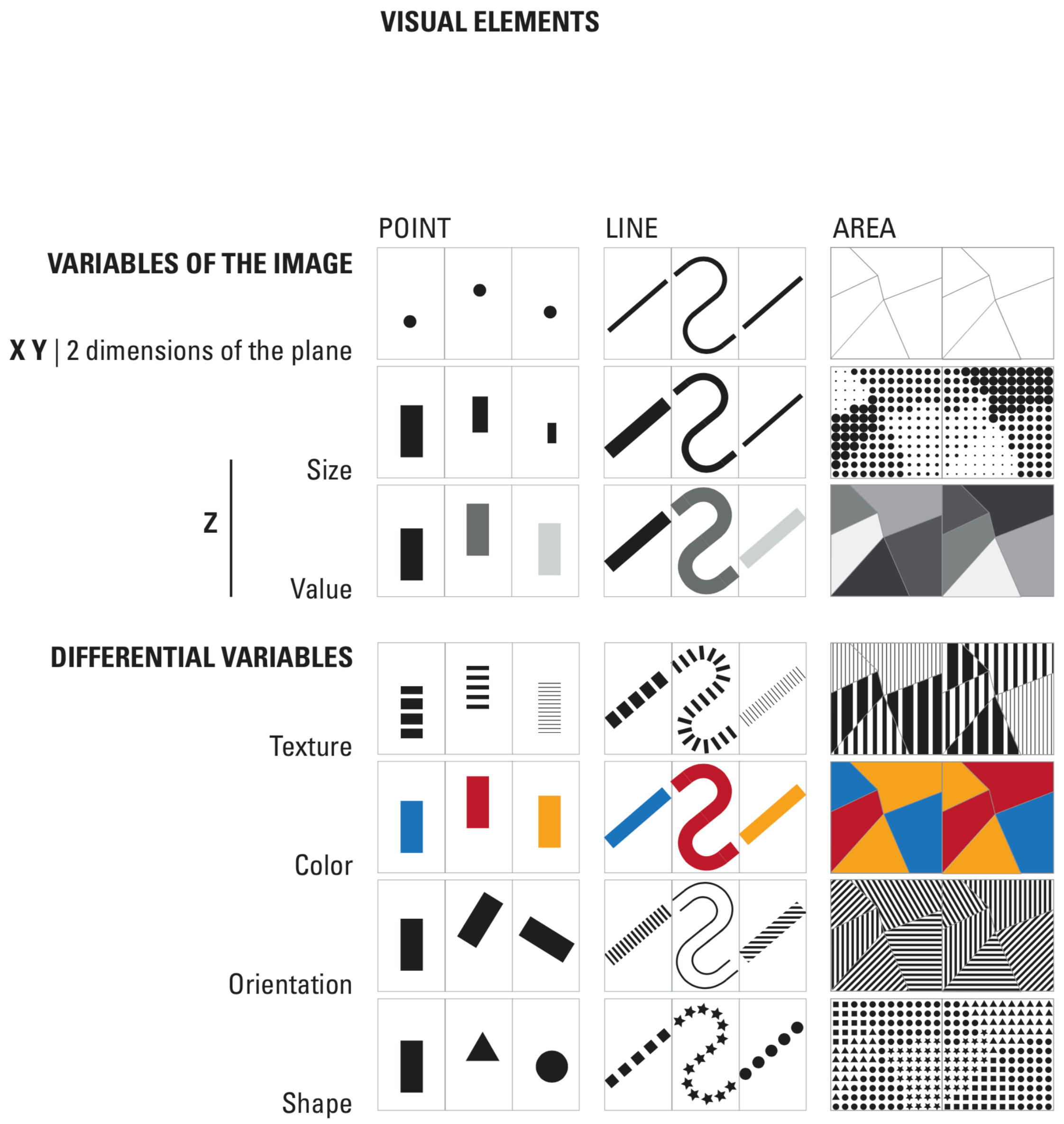
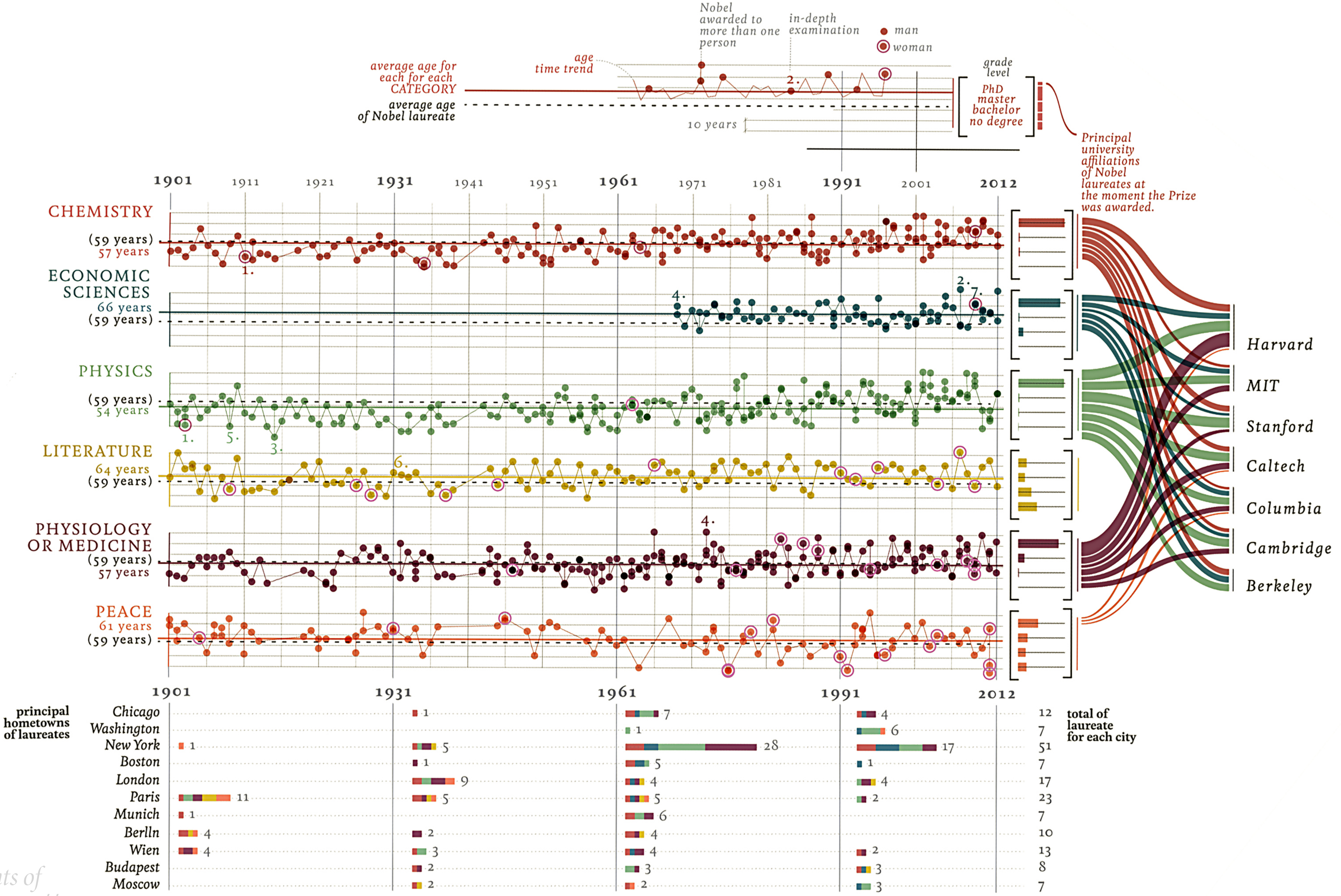
exercise, identify data encodings in visual channels





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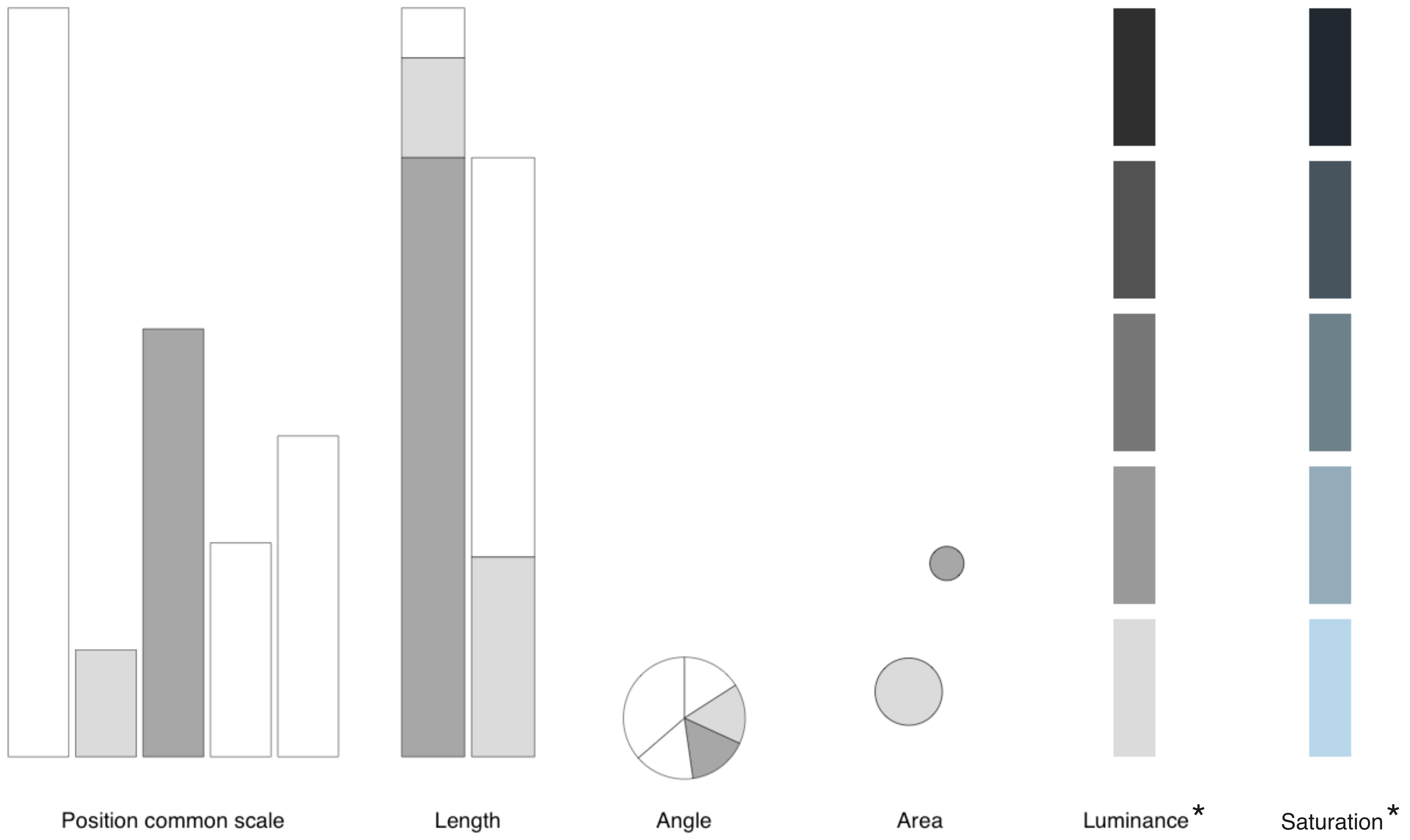
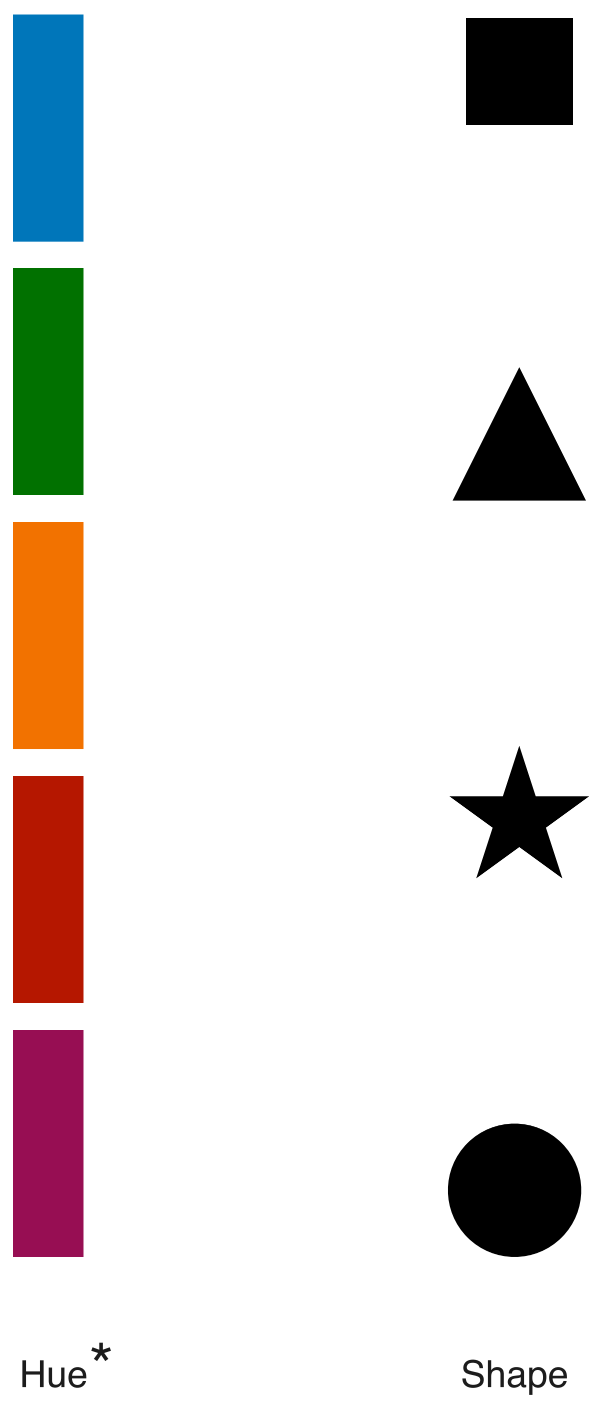
channel effectiveness for encoding data

ratio, interval, and ordered



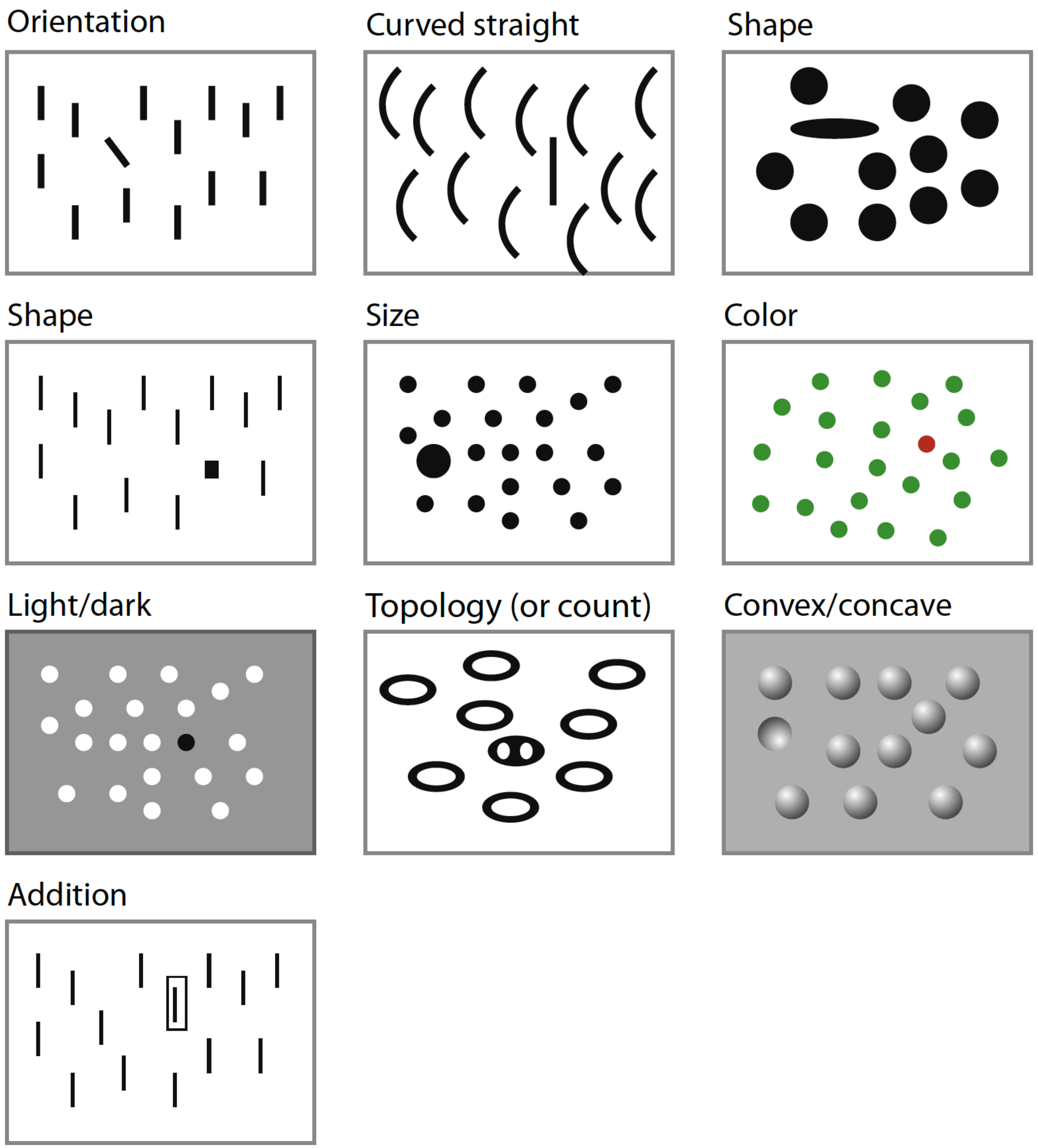
more effective ⟷ **less effective**

categorical

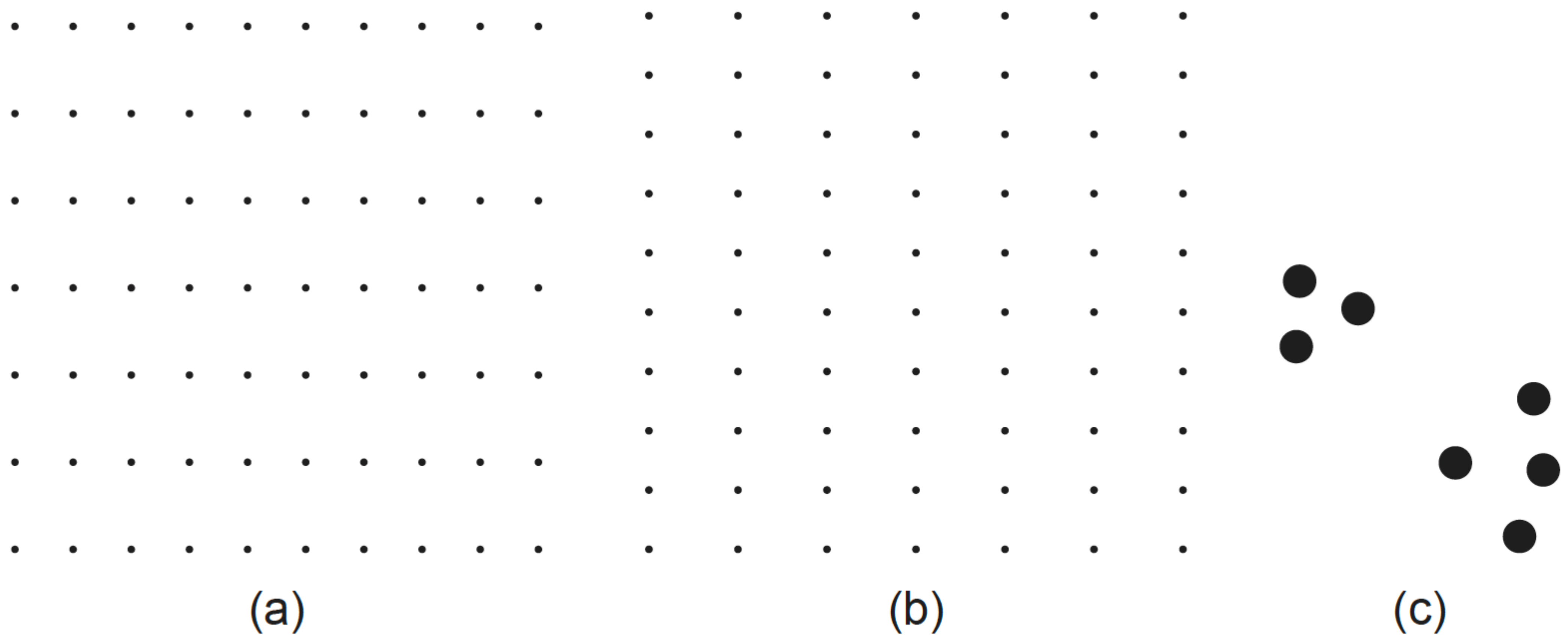


more effective ⟷ **less effective**

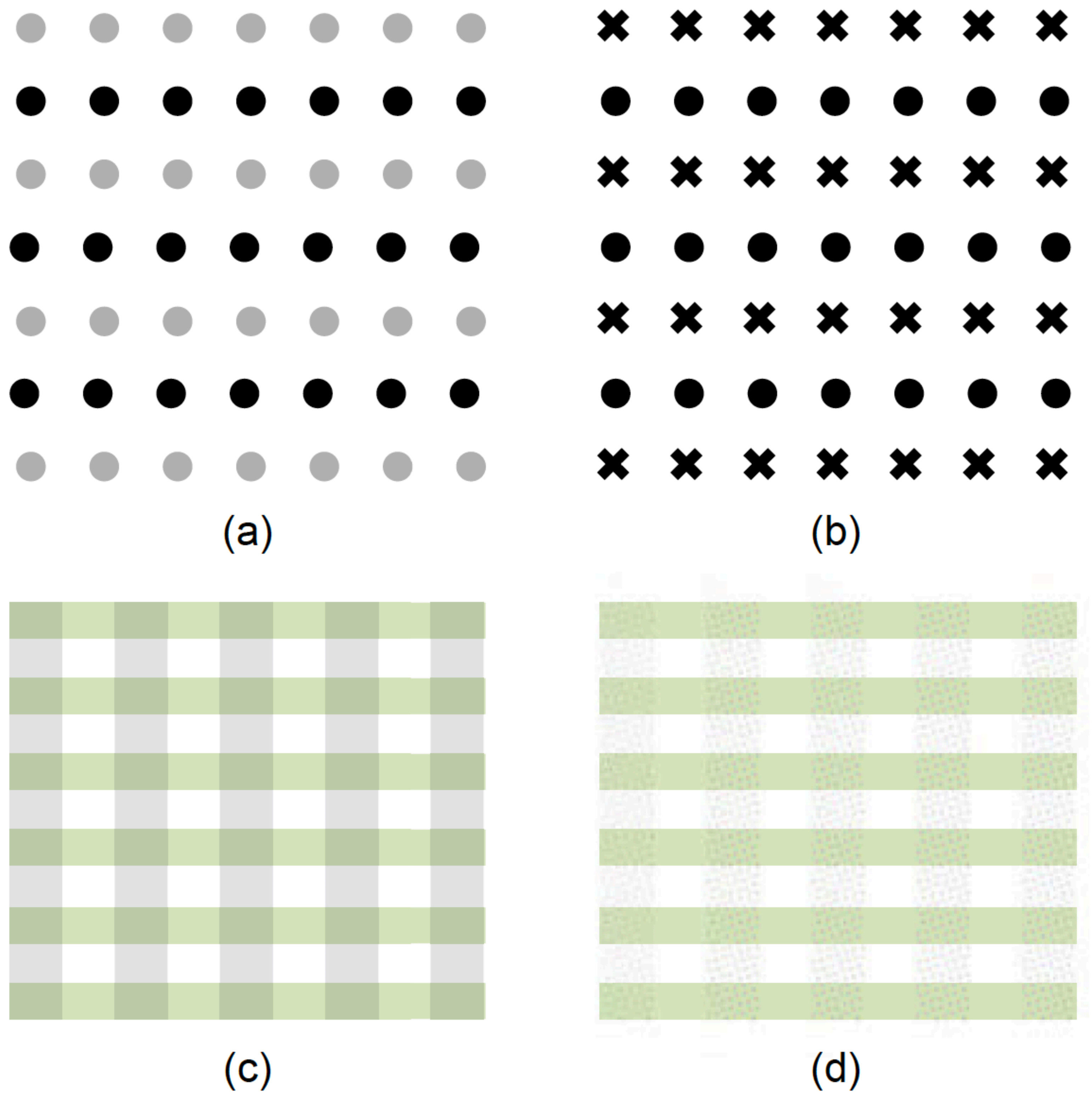
perceptual psychology


Orientation
Curved straight
Shape
Shape
Size
Color
Light/dark
Topology (or count)
Convex/concave
Addition

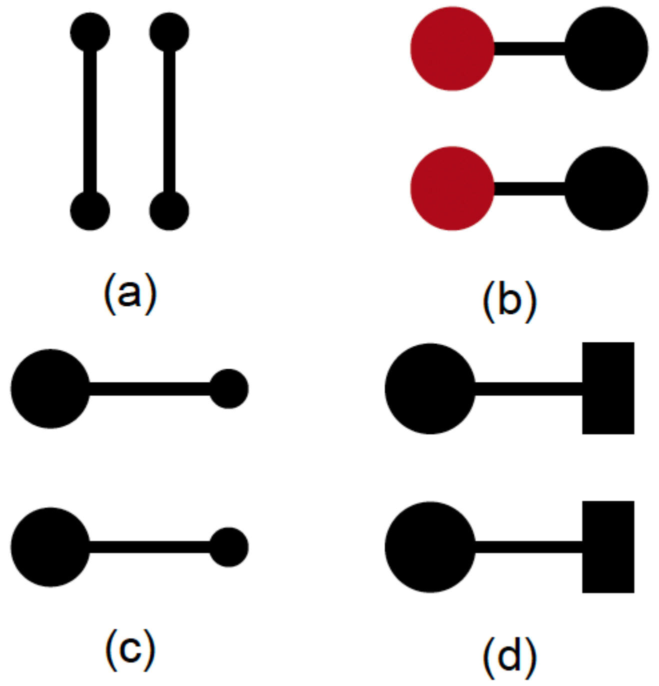
 Gestalt principles, *proximity*



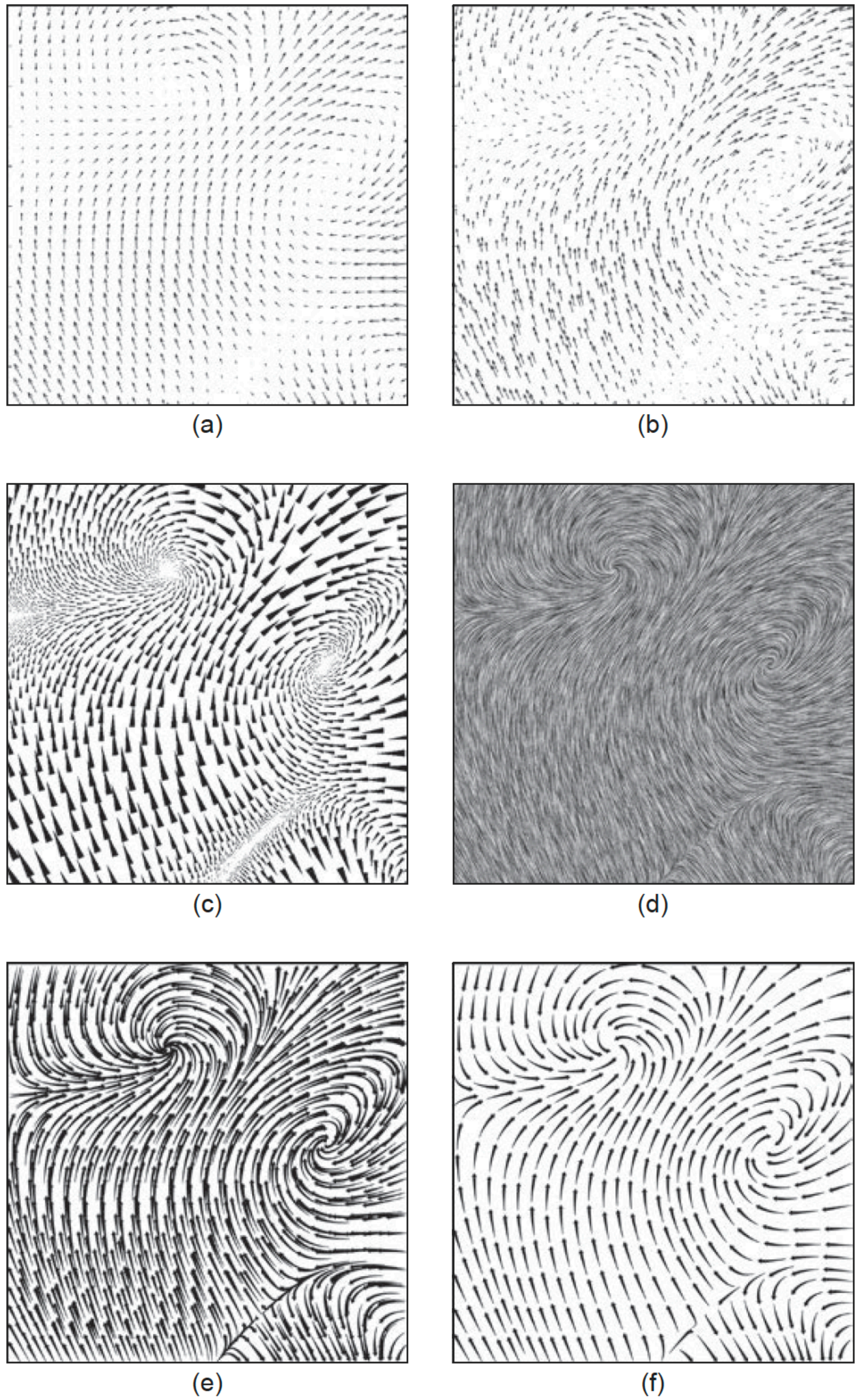
 Gestalt principles, *similarity*



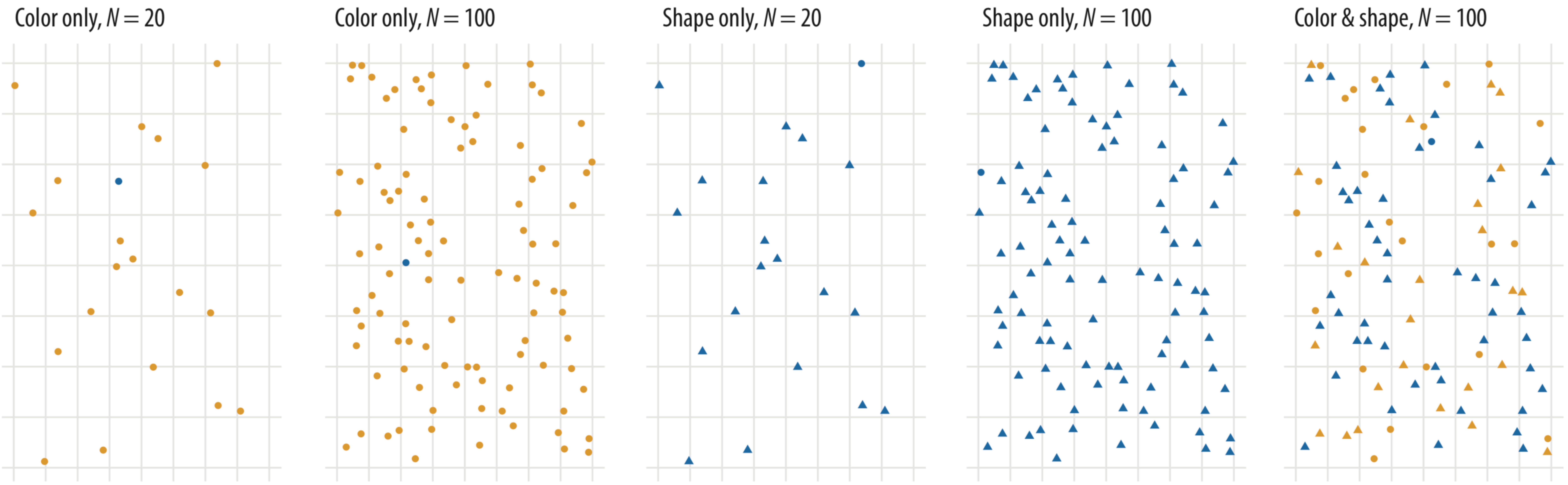
 Gestalt principles, ***connectedness***



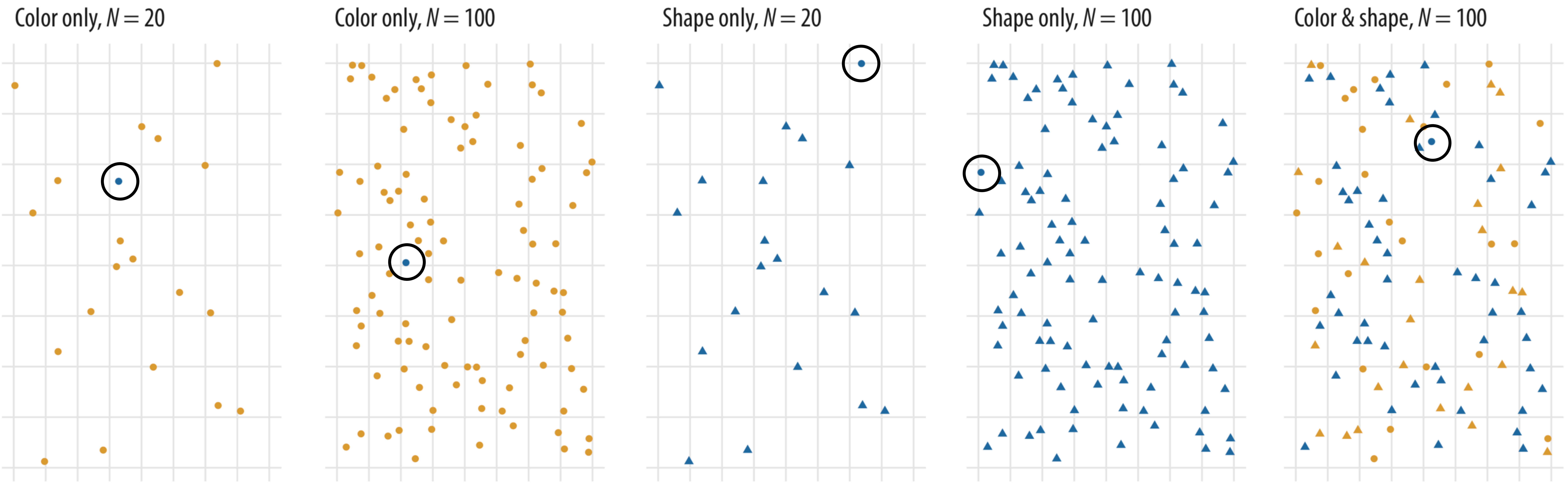
perceptual psychology, **Gestalt principles,** ***orientation, magnitude, direction***



 example — *focusing visual attention*



perceptual psychology, example — *focusing visual attention*



resources

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