Storytelling with data

05 | visual design, data encodings, perceptual psychology

Scott Spencer | Columbia University

course overview | main course deliverables

Why show data graphically?

why data graphics, **graphic of a datum — effective? Conveys meaning?**

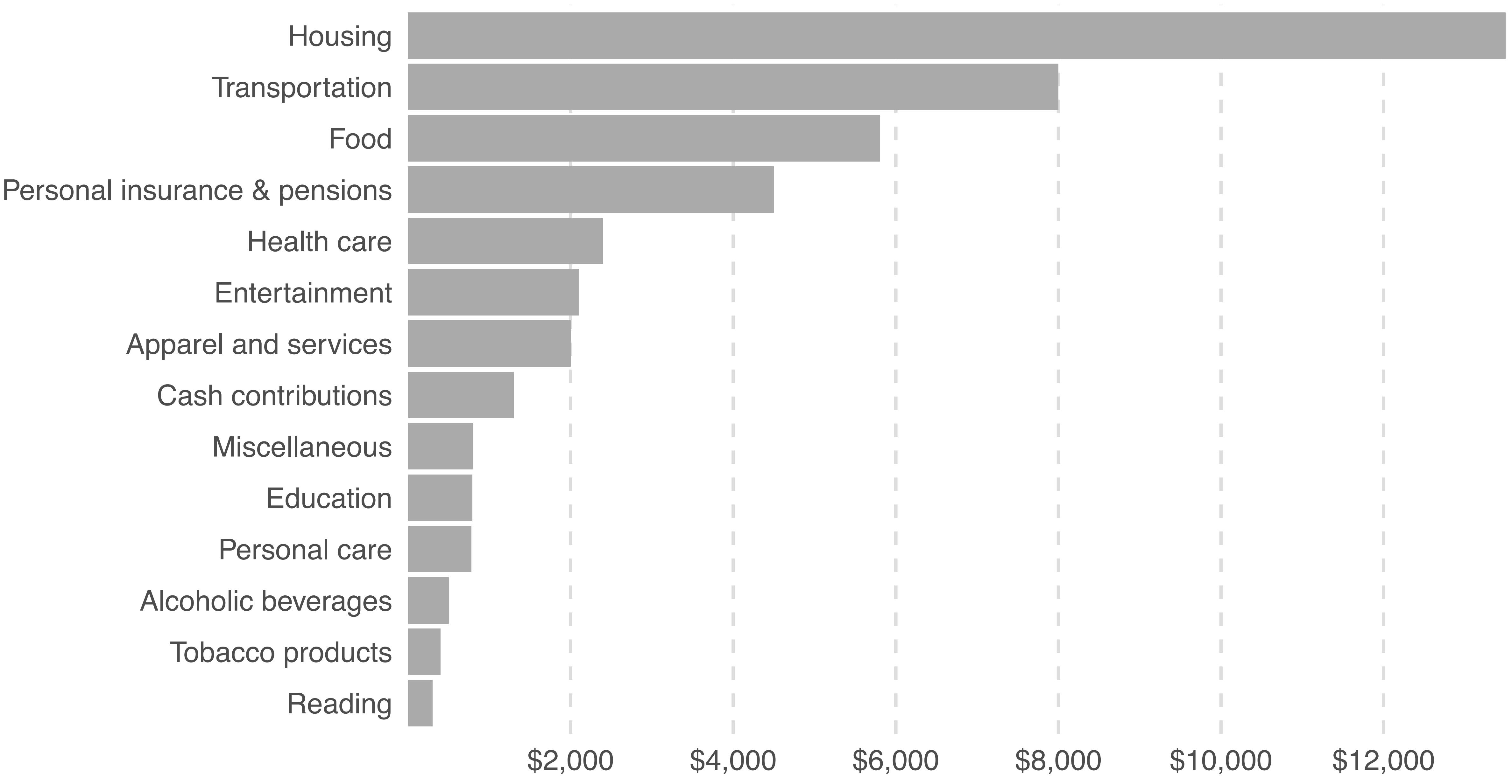

Fig. 3. Major categories of expenditures, descending dollar value, 2002 U.S. Consumer Expenditure Survey

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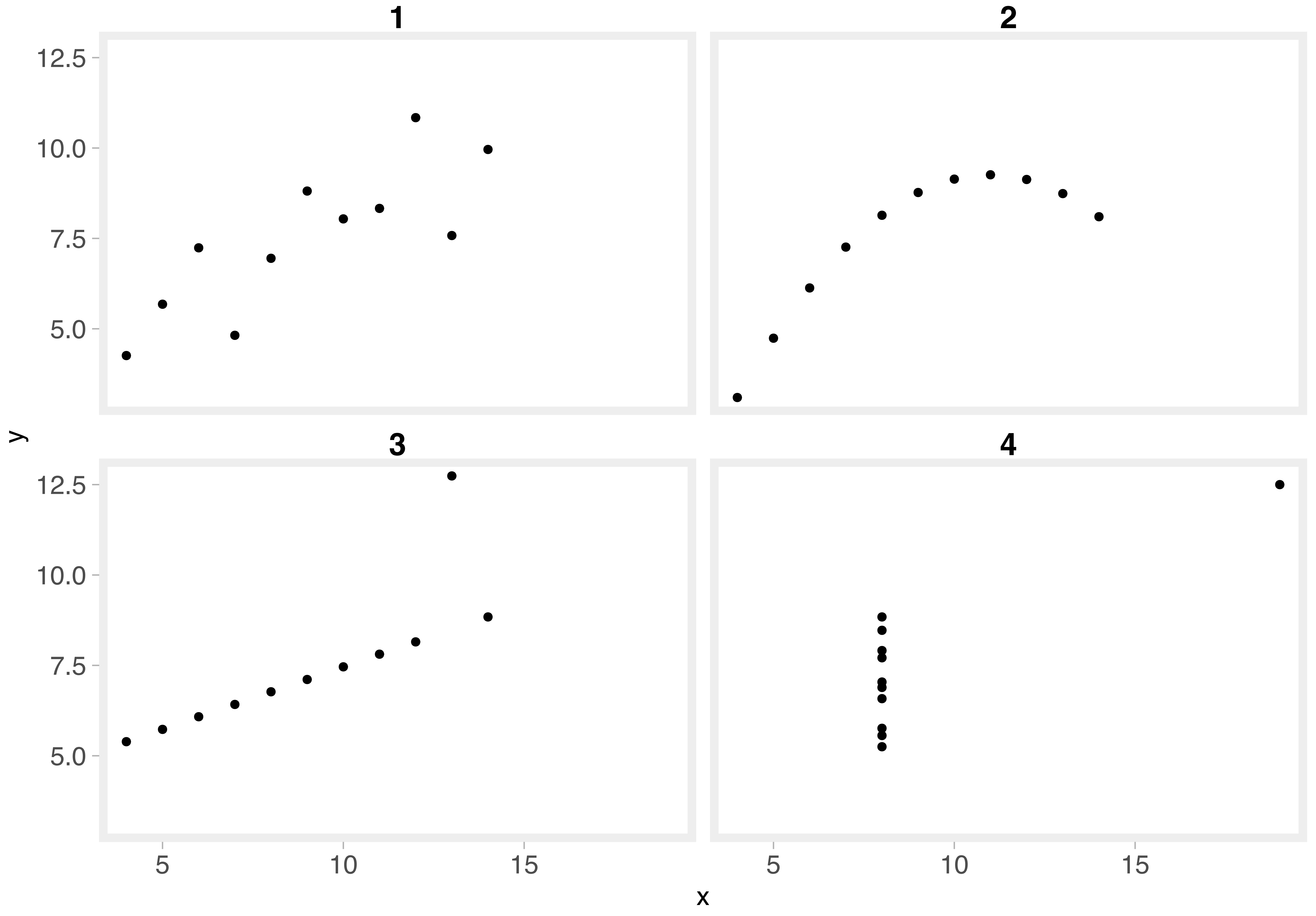
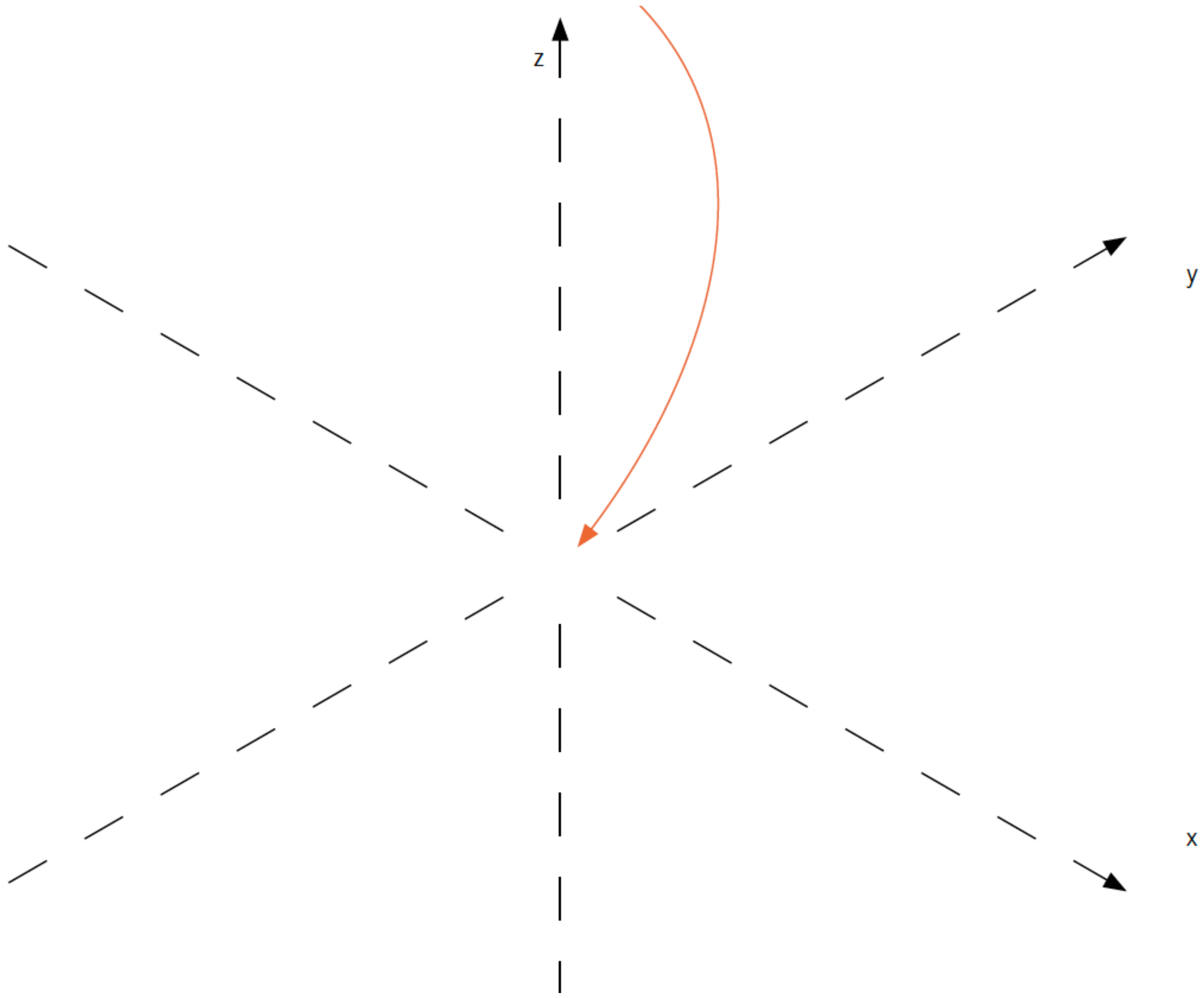
With graphics we can use our natural ability to see patterns through visual comparison

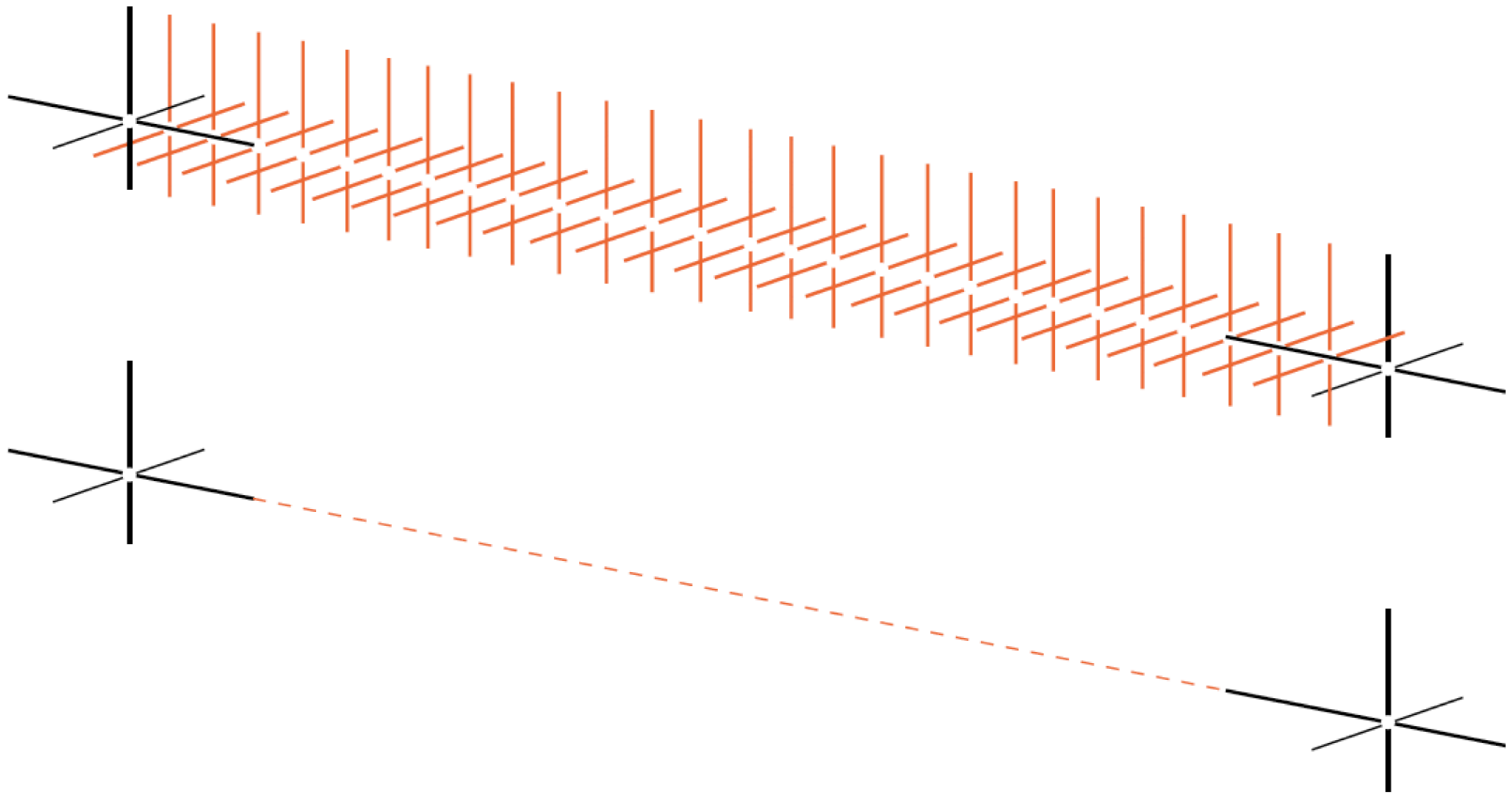


graphic design concepts

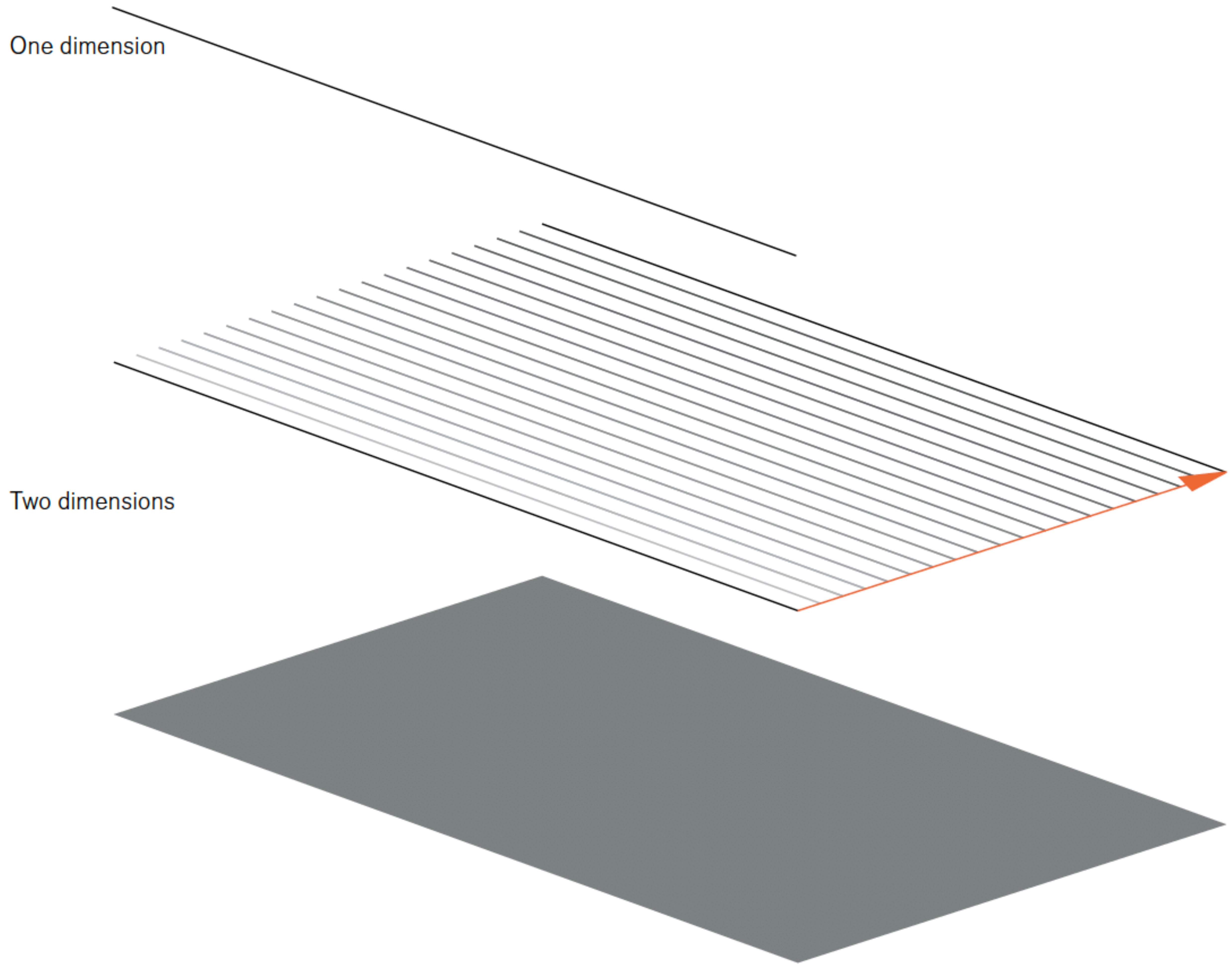
 geometry of graphical elements — point



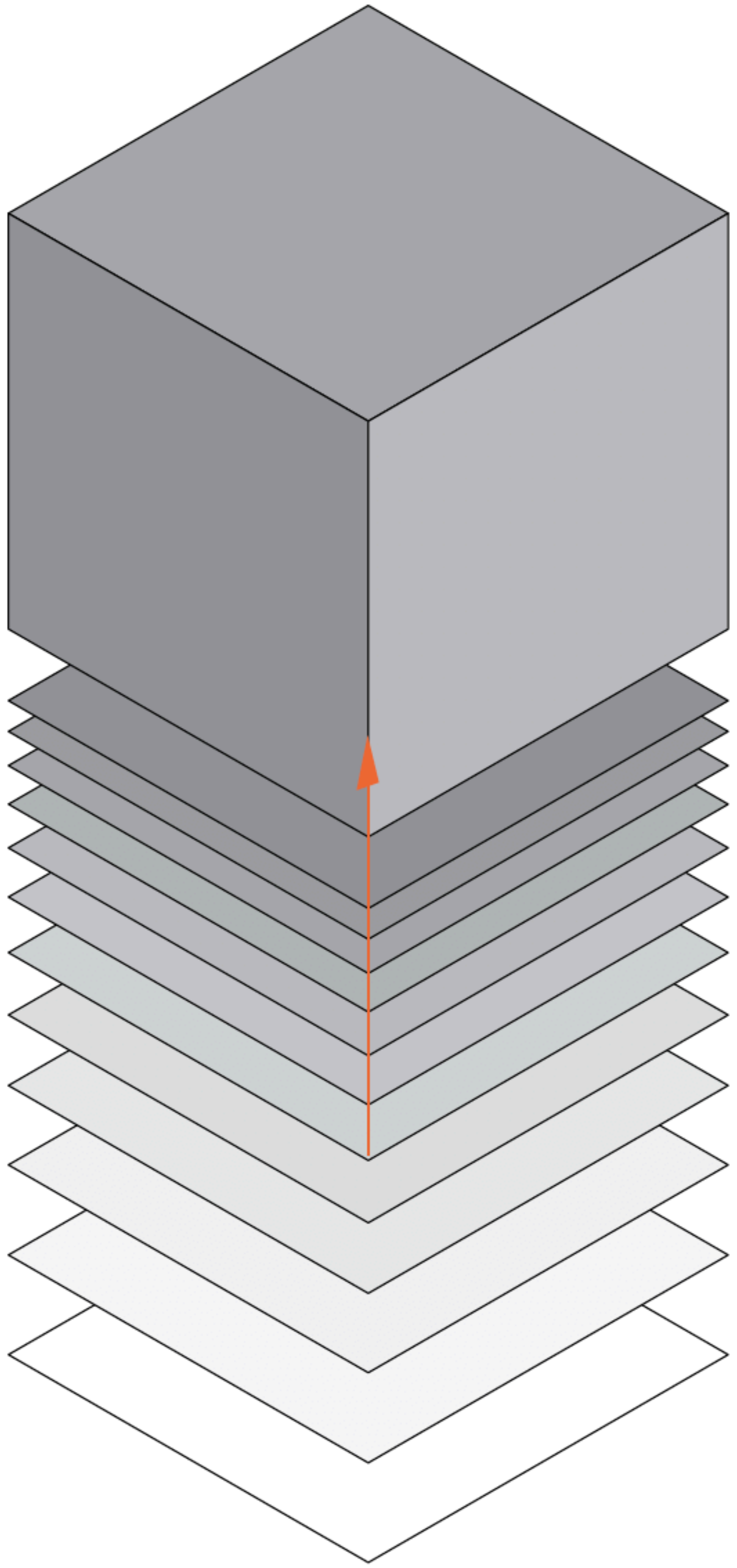
data encodings, geometry of graphical elements — line



data encodings, geometry of graphical elements — surface



 geometry of graphical elements — volume



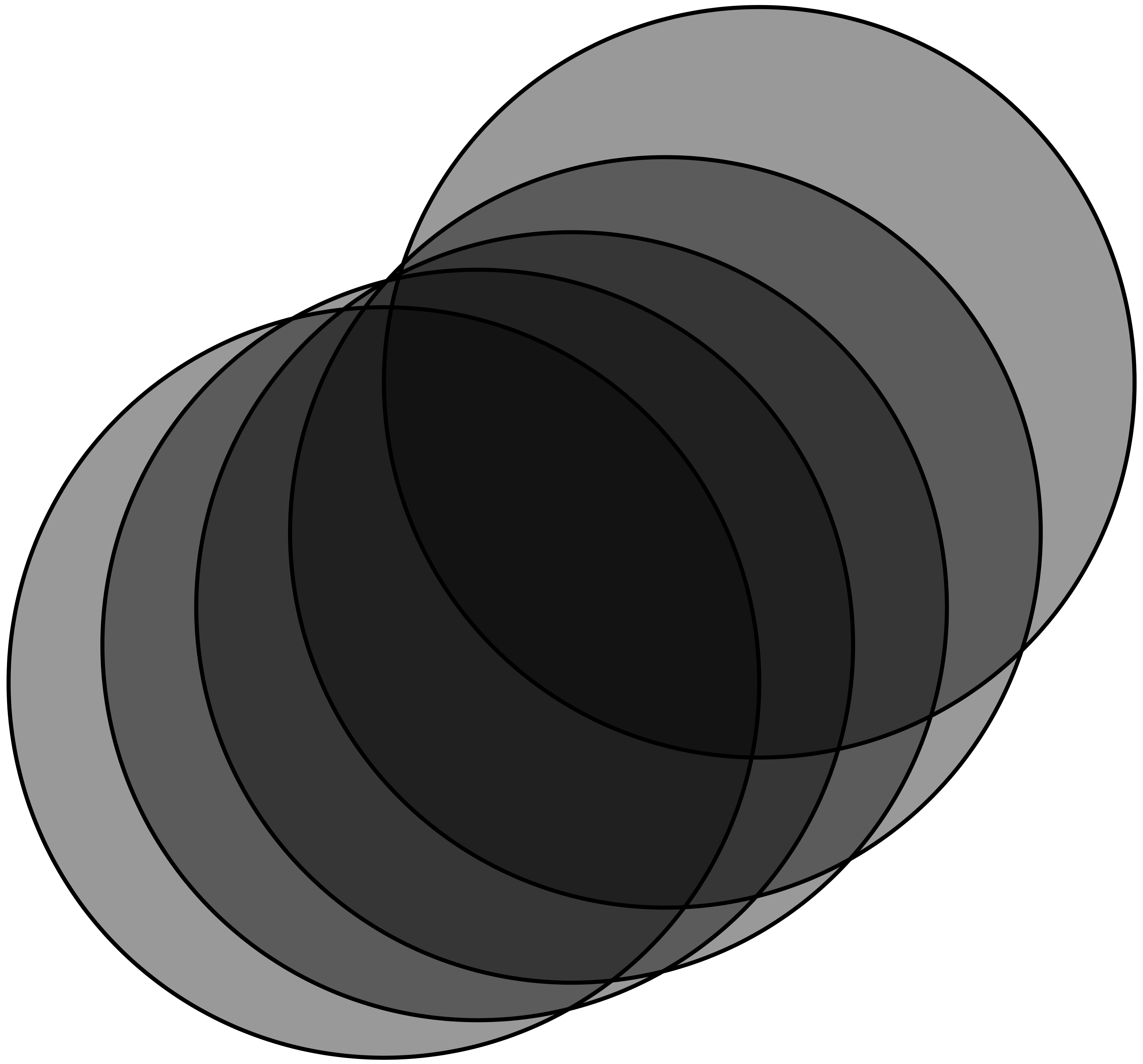
data encodings, layering — order of elements determines position towards reader and when overlapping, occlude

```
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")
```

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

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

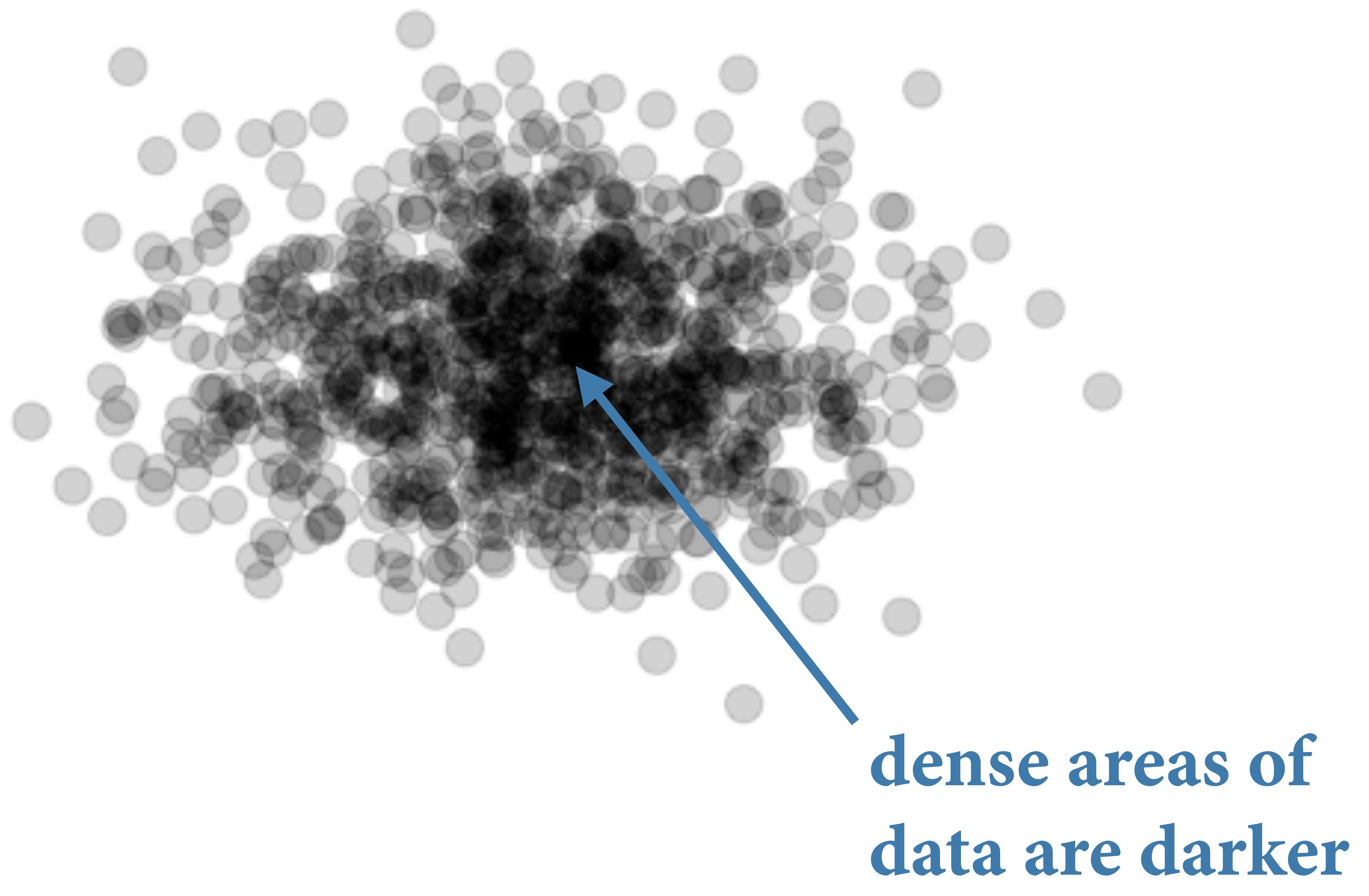
```
ggplot() +
  theme_void() +
  coord_equal() +
  ggforce::geom_circle(aes(
    x0 = seq(from = 0, to = 1, length.out = 5),
    y0 = c(0, .1, .2, .4, .8),
    r = 1
  ),
  fill = "#000000",
  alpha = 0.4)
```



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() +
  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",
             alpha = 0.4) +
  geom_point(aes(x = 1, y = 1),
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             alpha = 0.4)
```
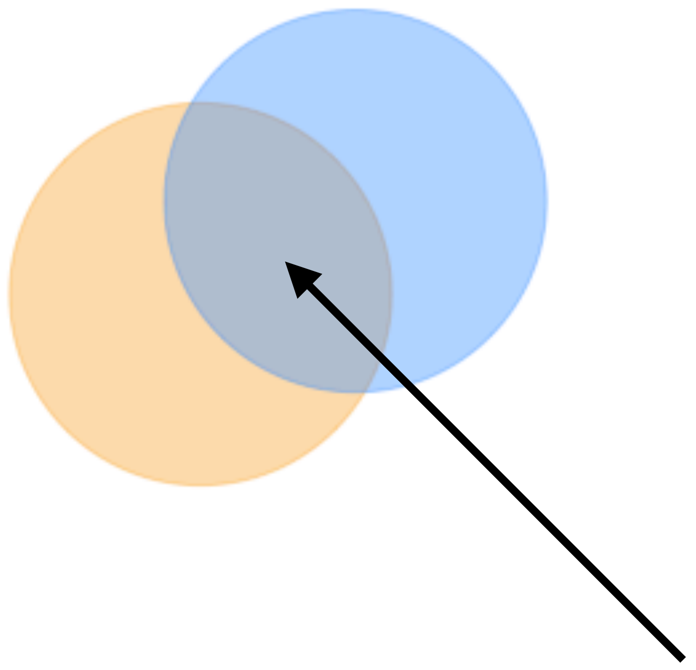
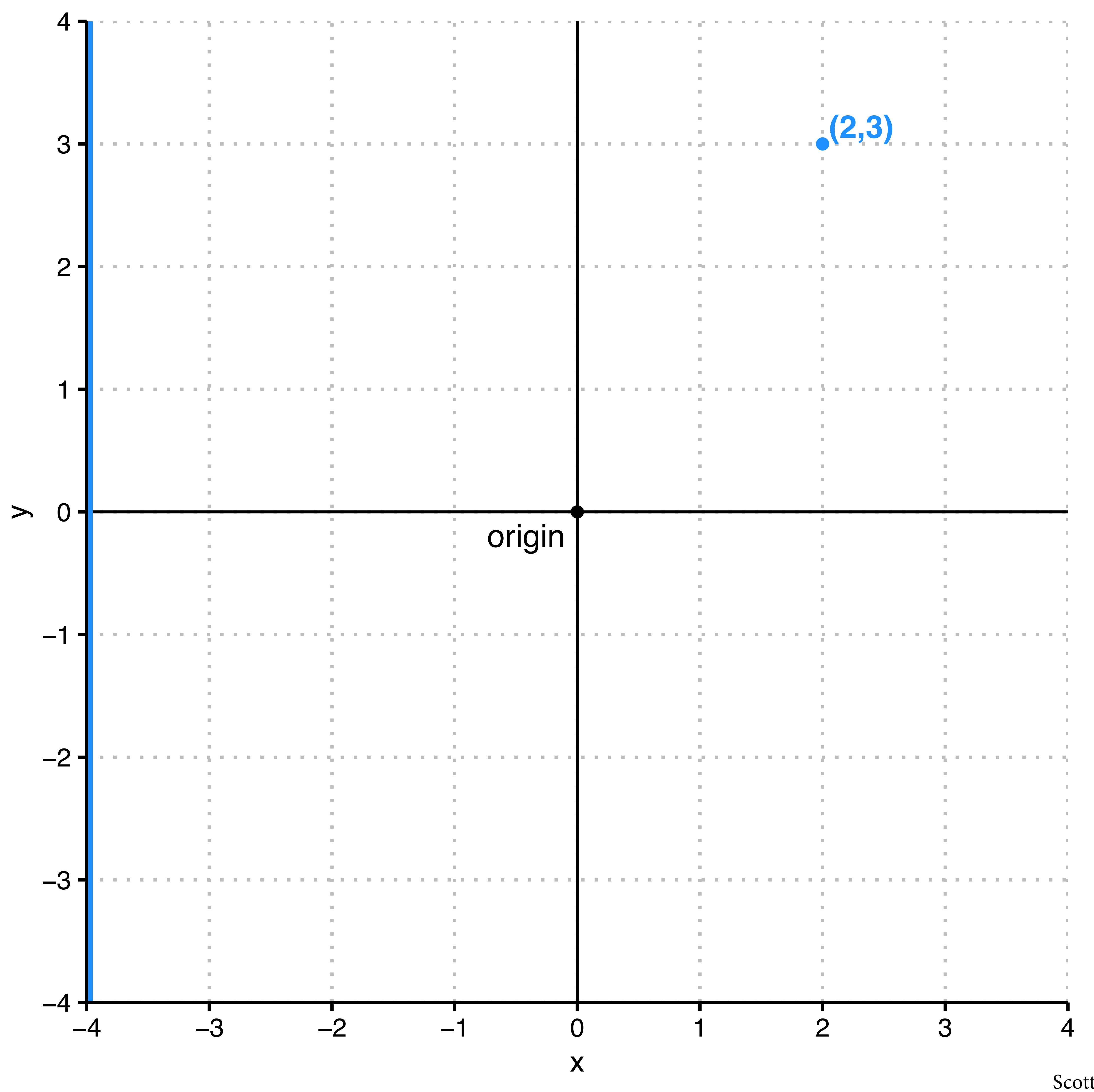



I didn't encode data with *this* color!?

graphs — coordinate systems and scales

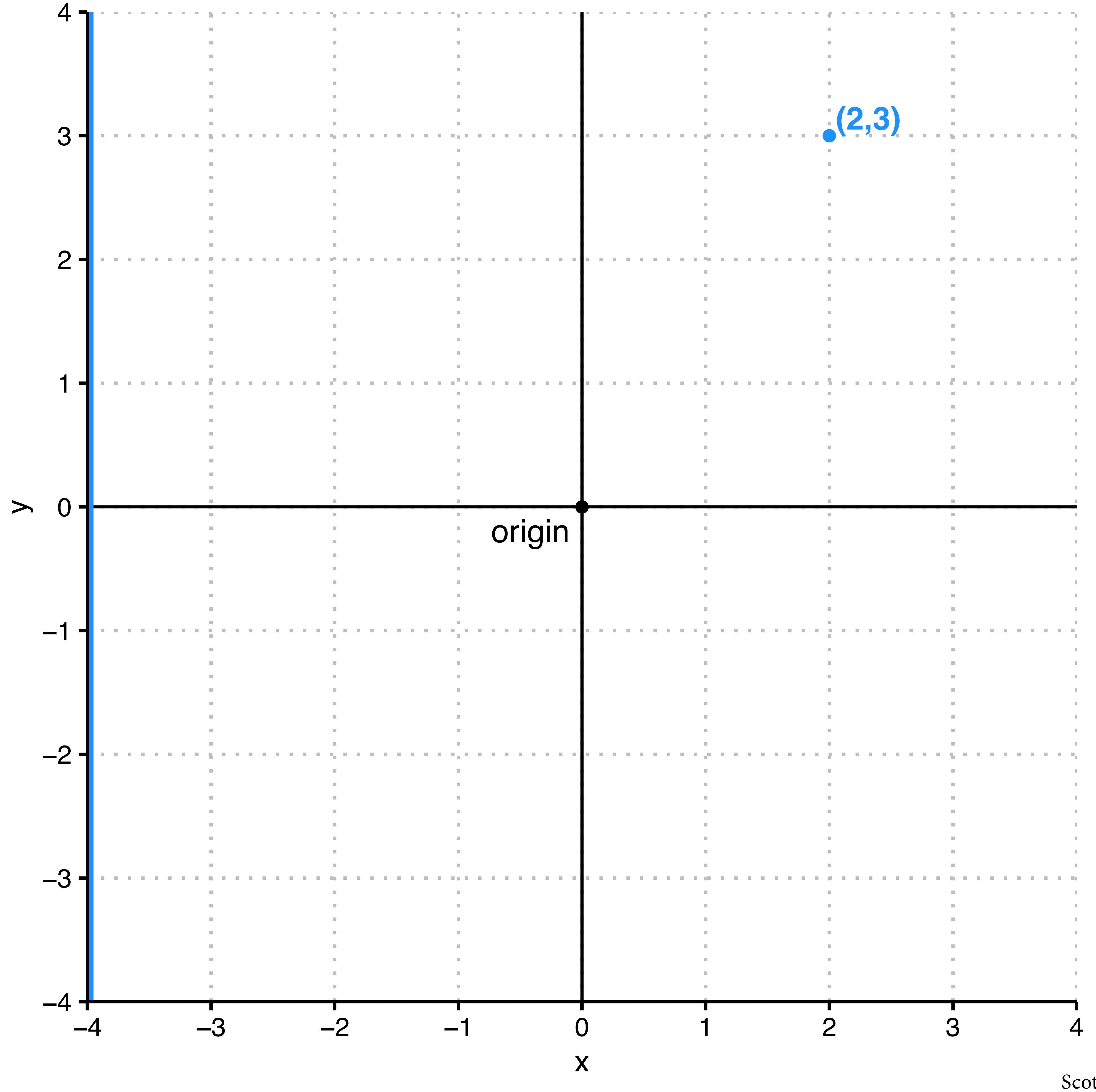
coordinates and scales, *two-dimensional Cartesian* coordinates — x and y axes run orthogonally to each other, and data values placed along linear axes

cartesian coordinates

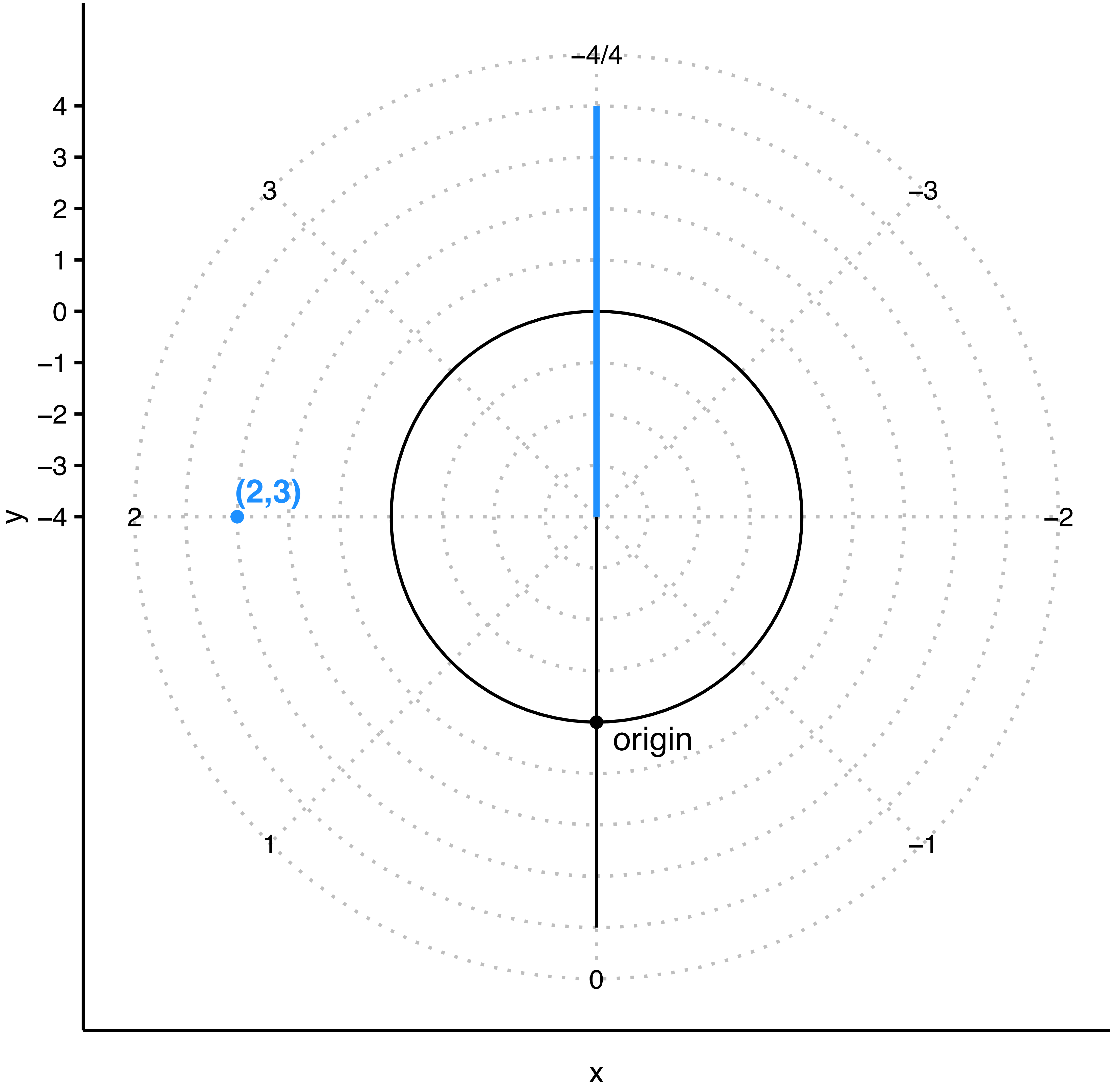


 ***other* coordinate systems are sometimes more effective in conveying information**

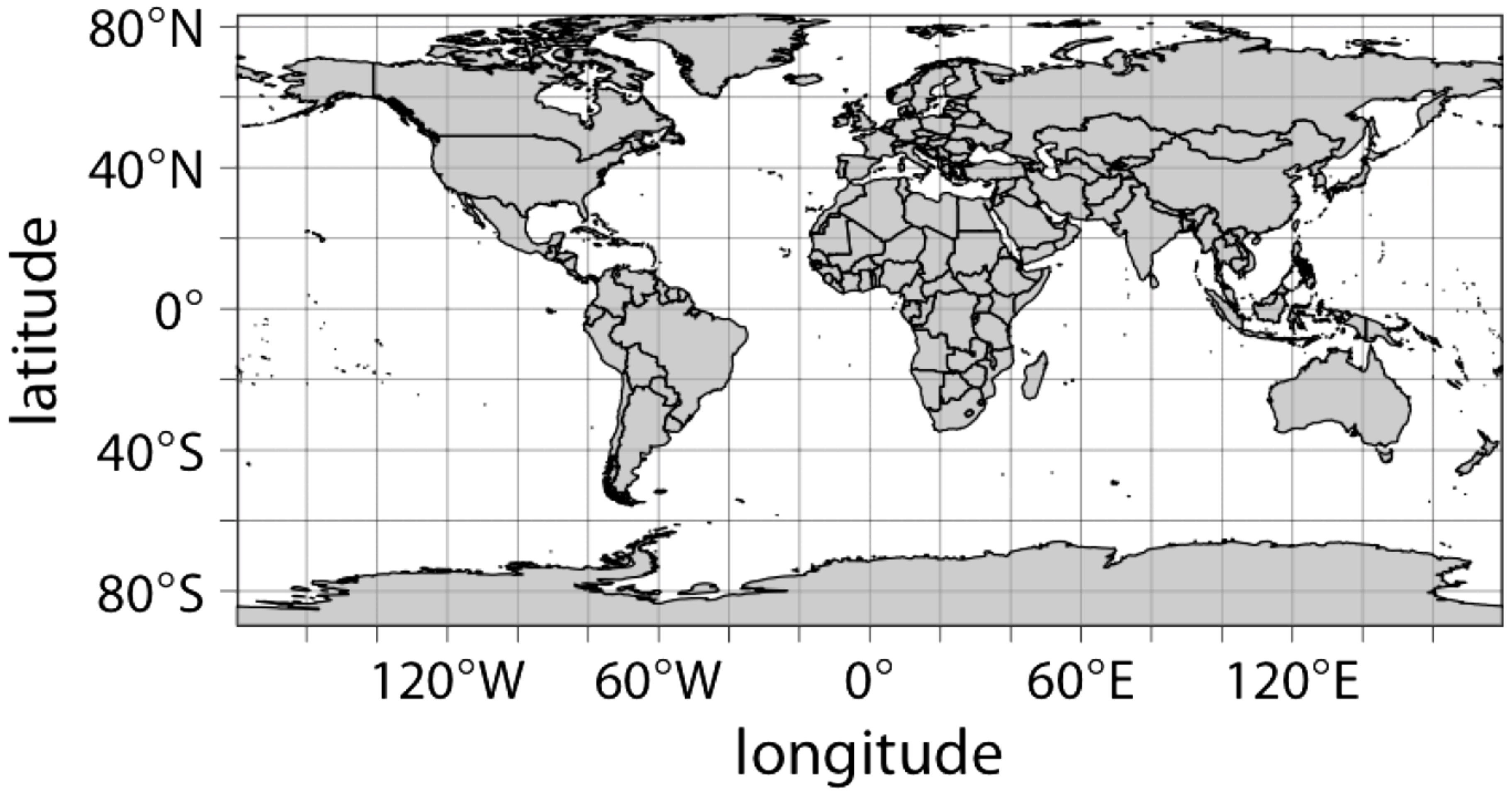
cartesian coordinates



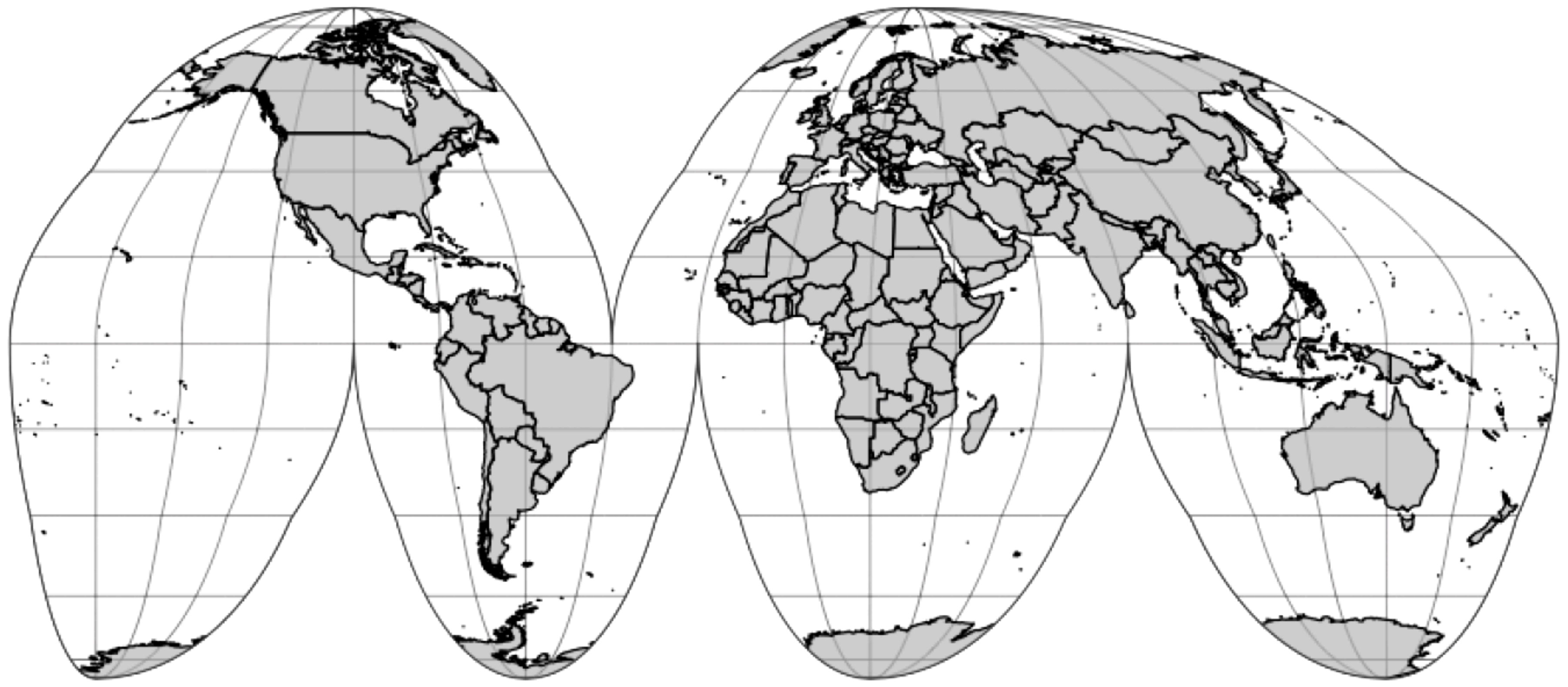
polar coordinates



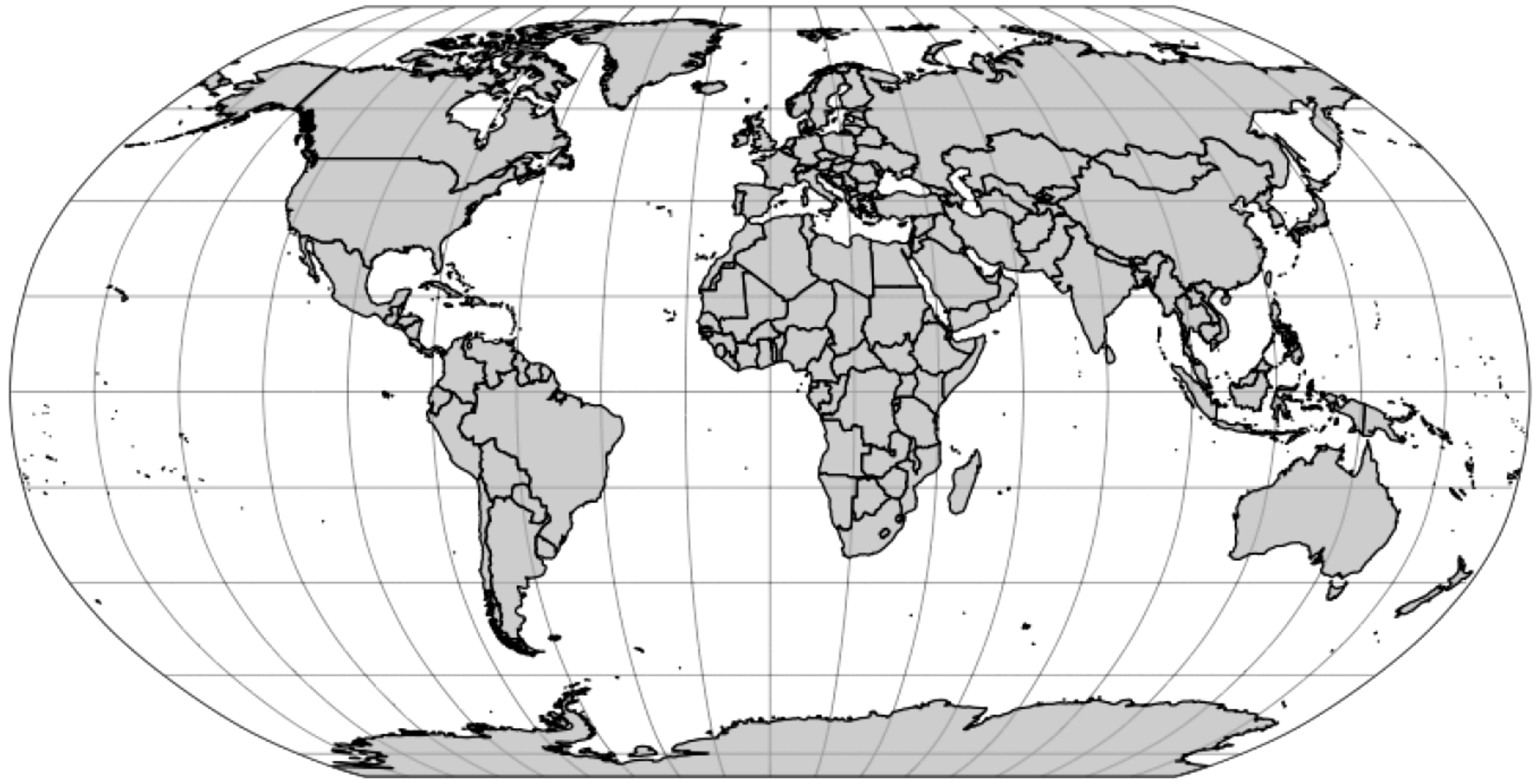
Cartesian longitude and latitude



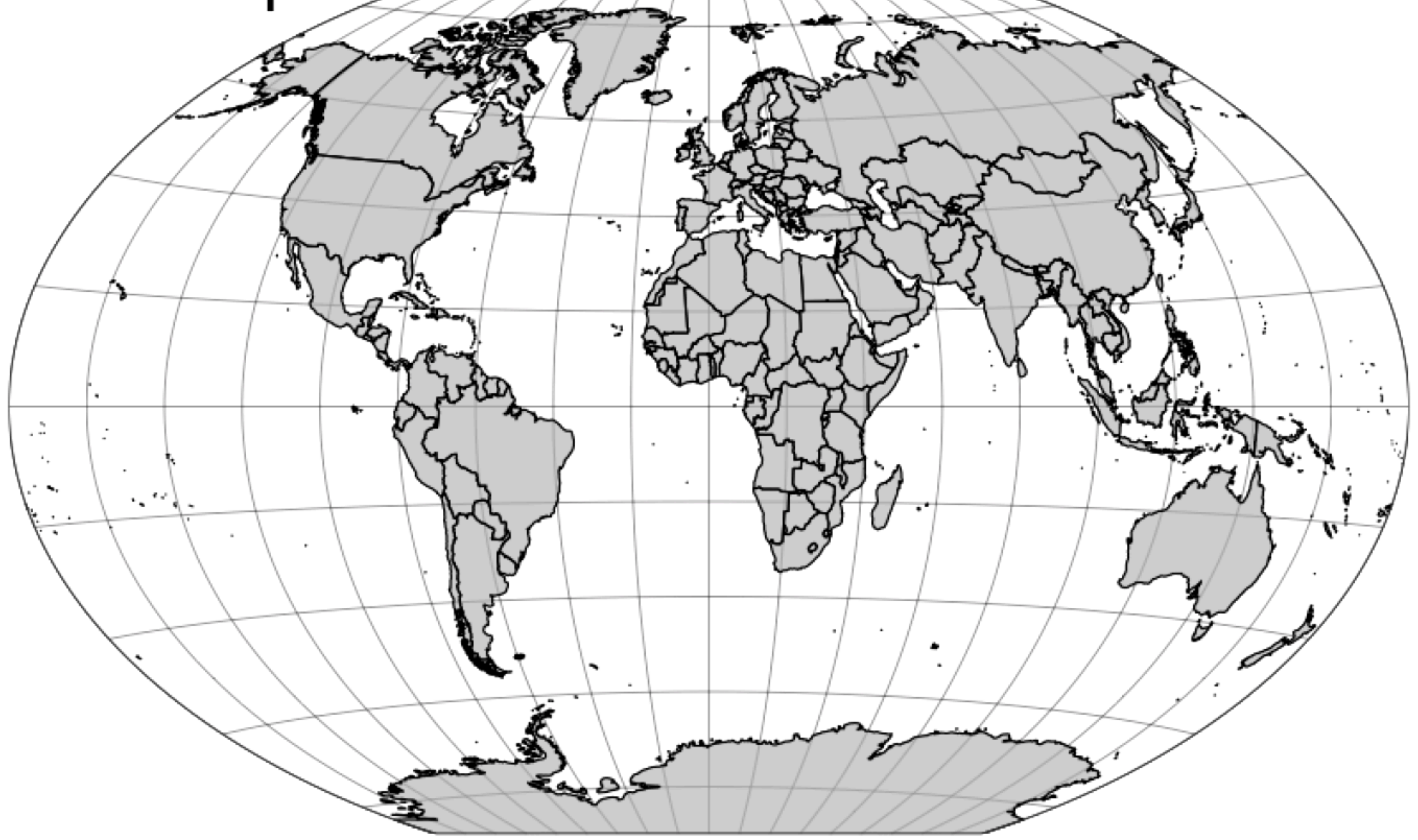
Interrupted Goode homolosine



Robinson

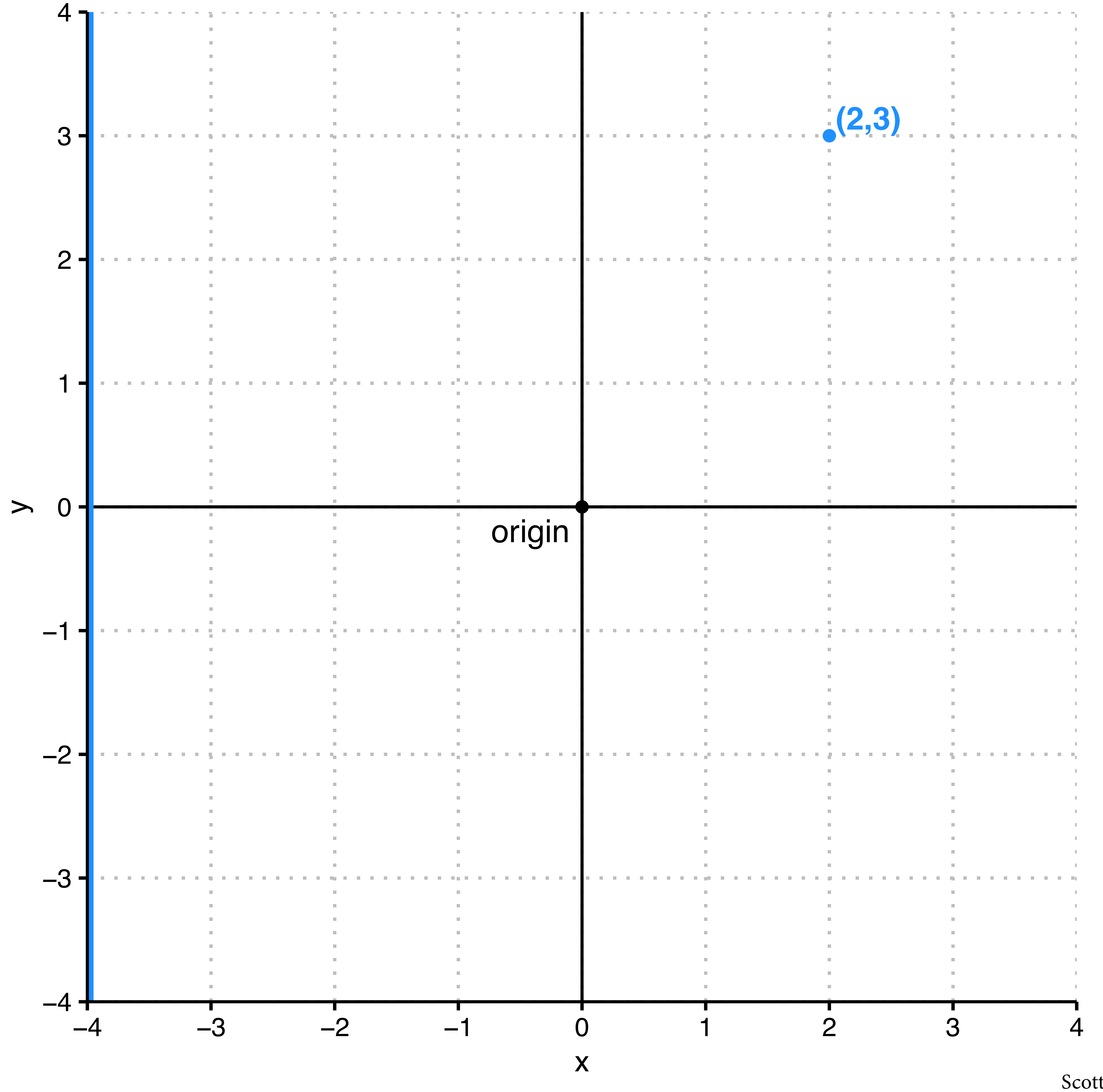


Winkel tripel

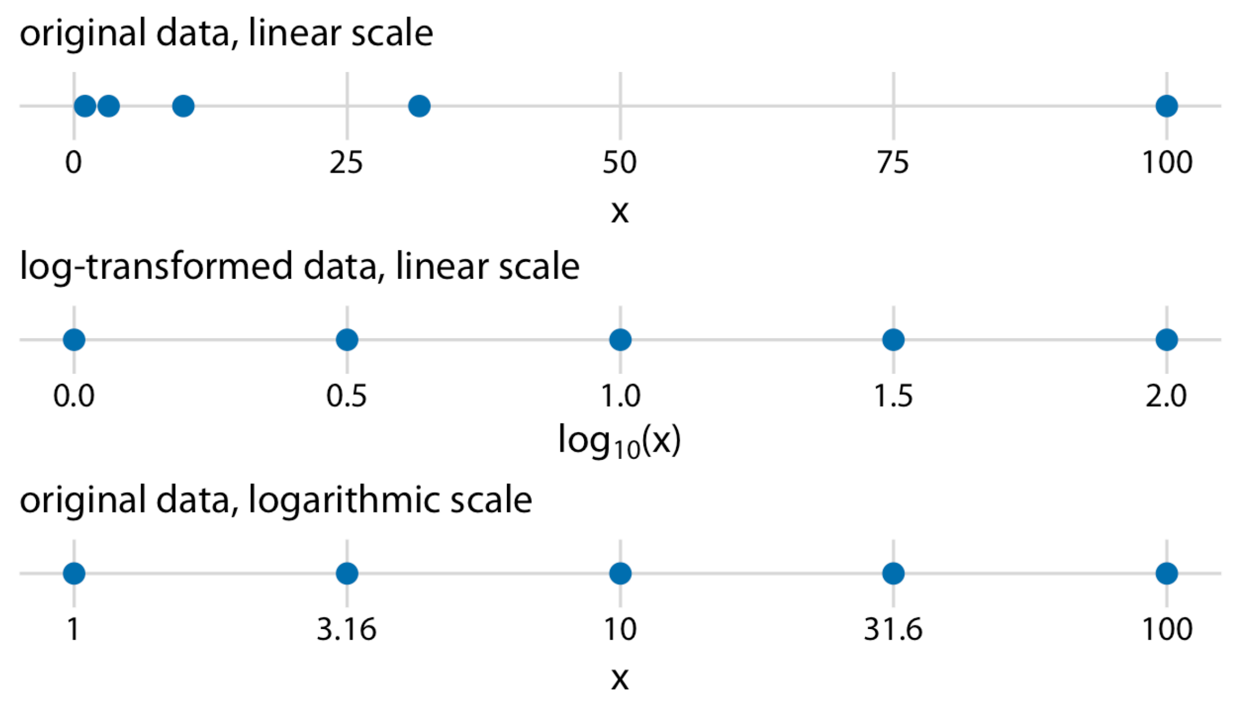


coordinates and scales, as with choosing coordinates, we can *transform* ***scales for data or axes*** for better understanding

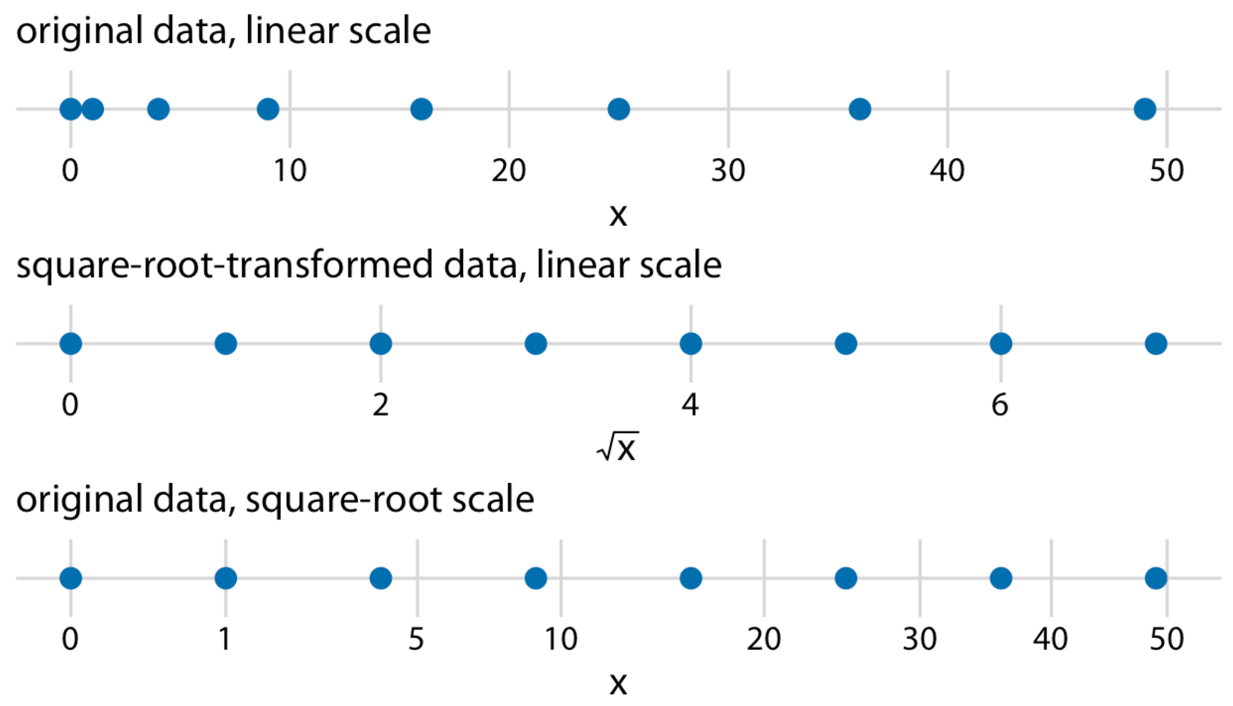
linear ***scales*** on cartesian coordinates



example — *log transforms*

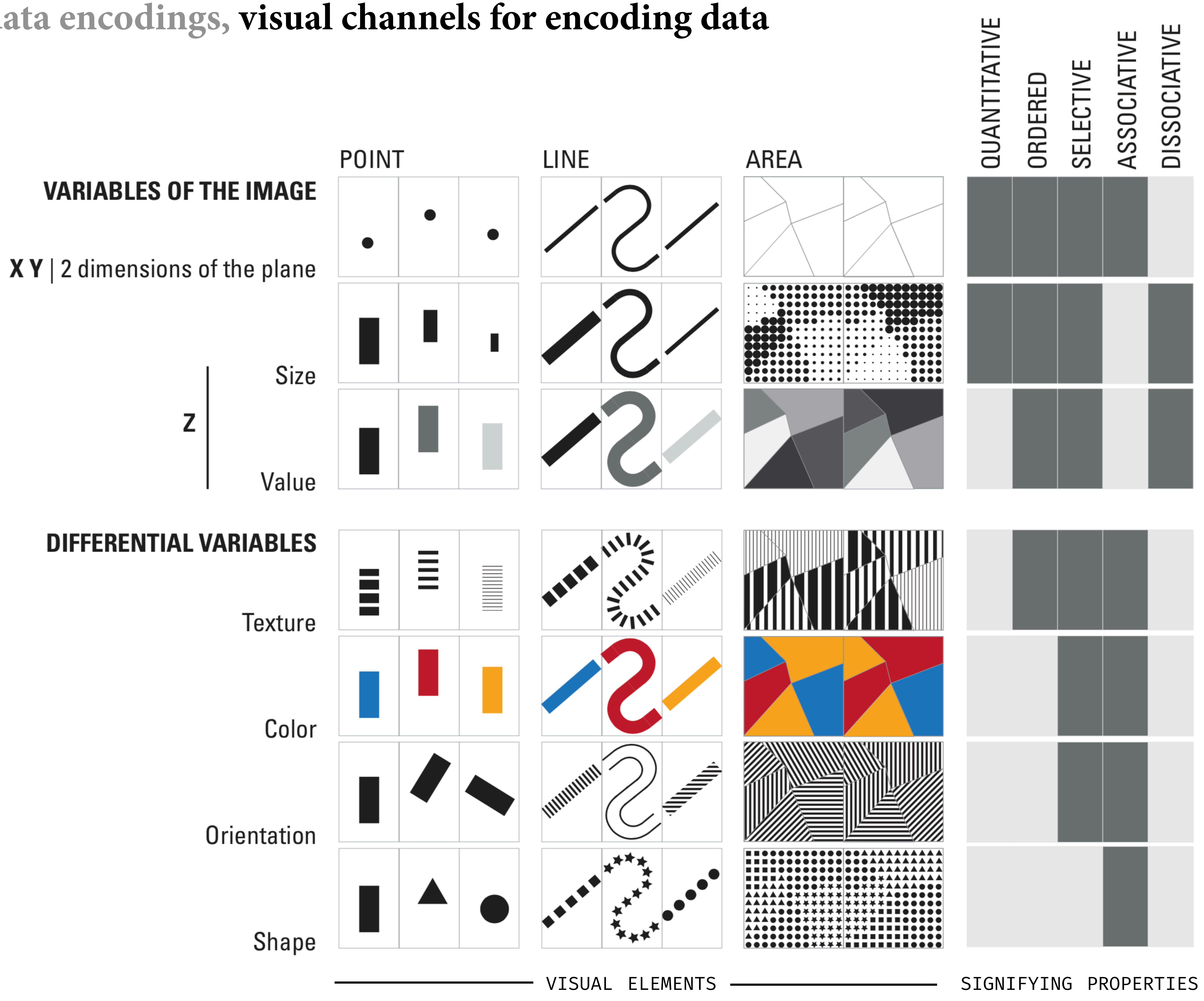


example — *square-root transforms*



data encodings for visual comparison

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



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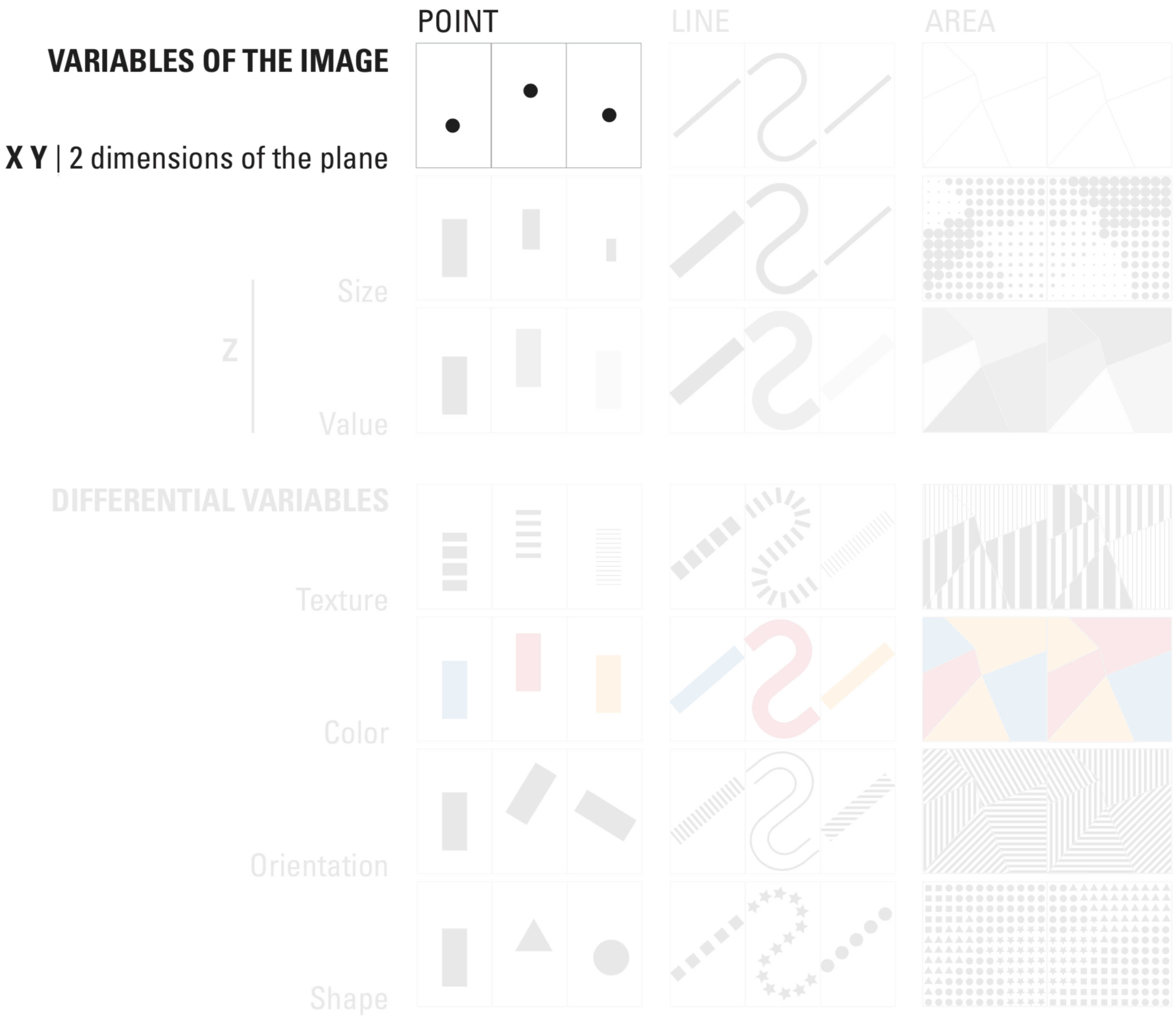
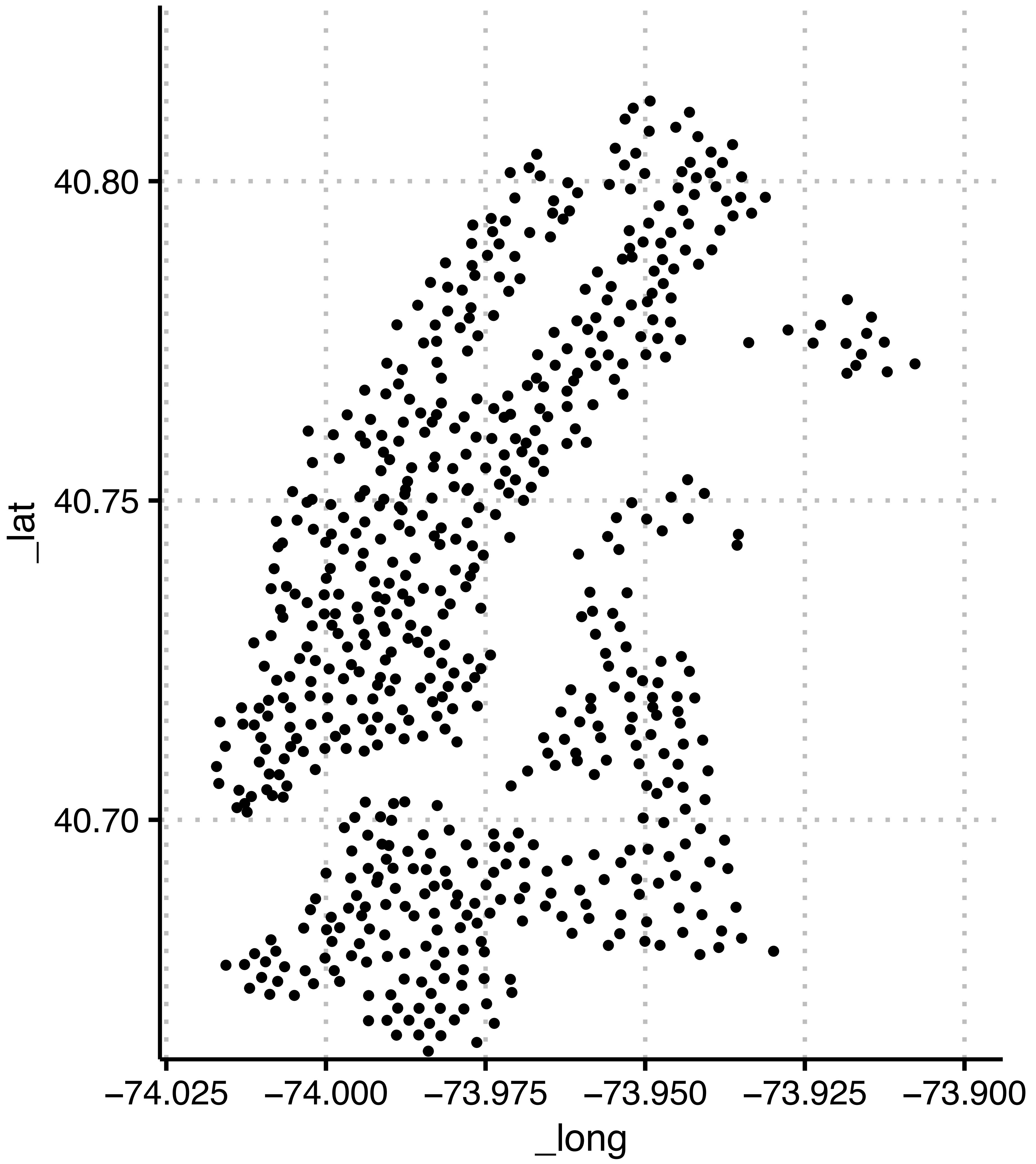


Citi Bike example — *exploratory data analysis*



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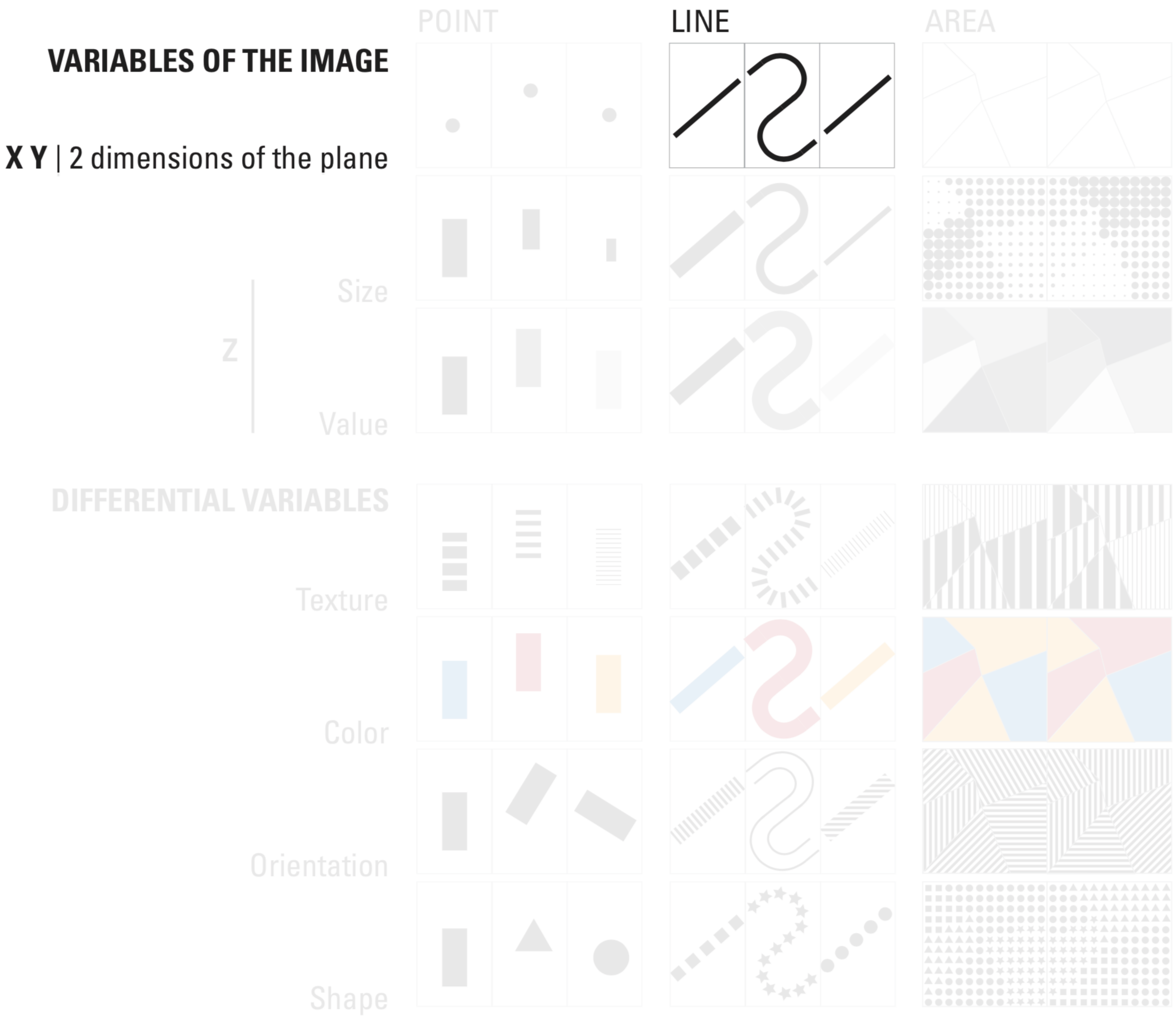

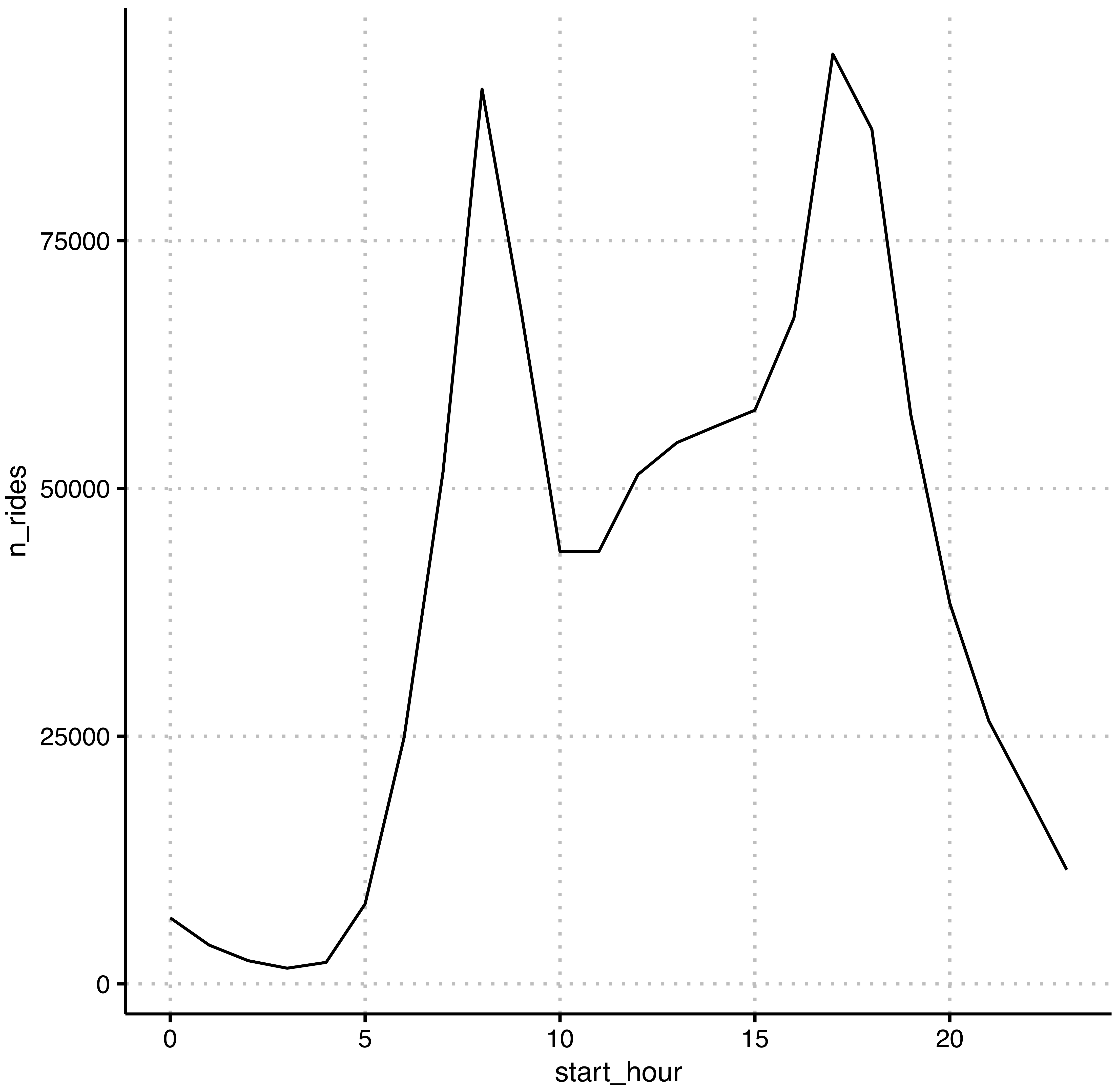

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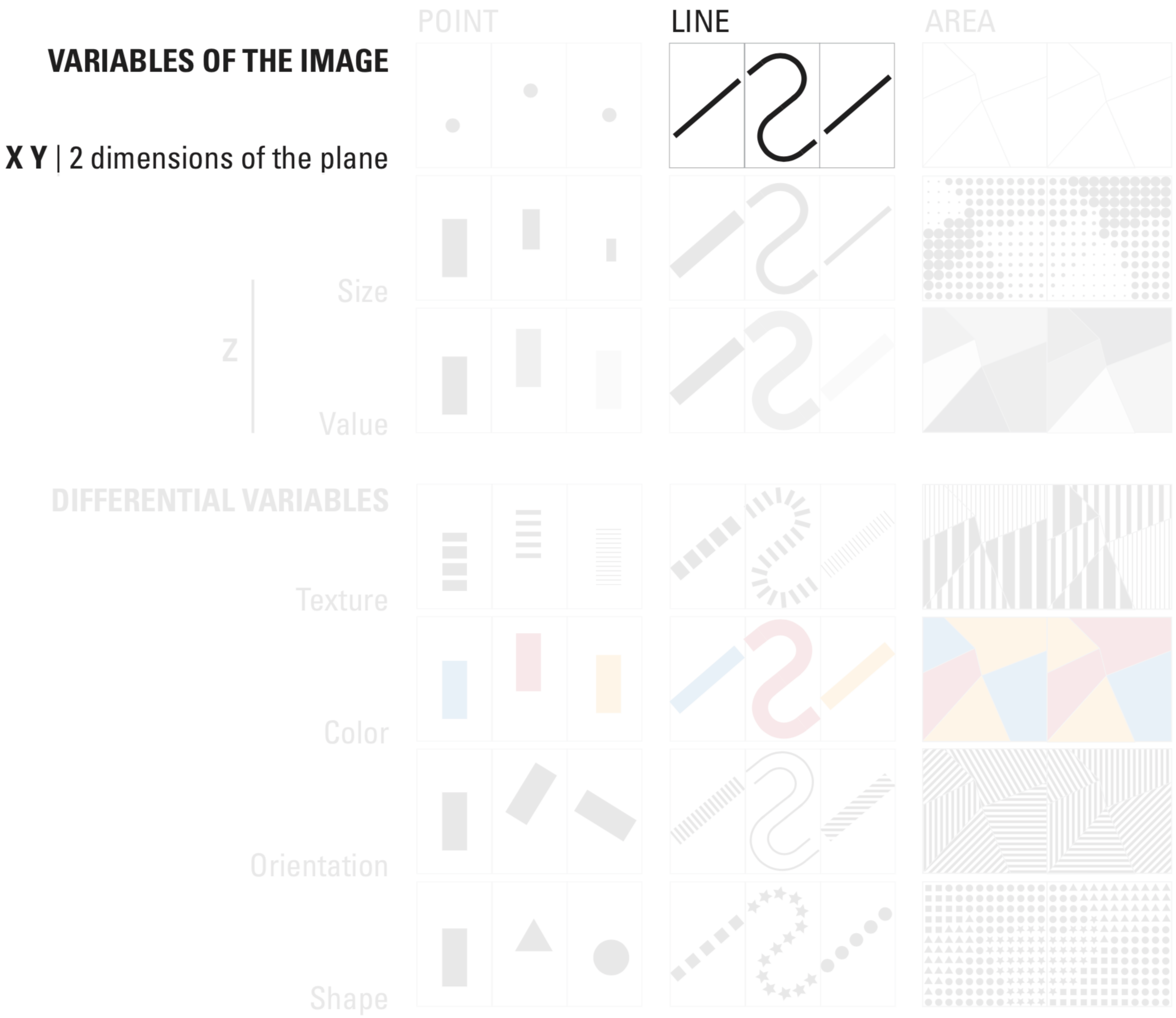
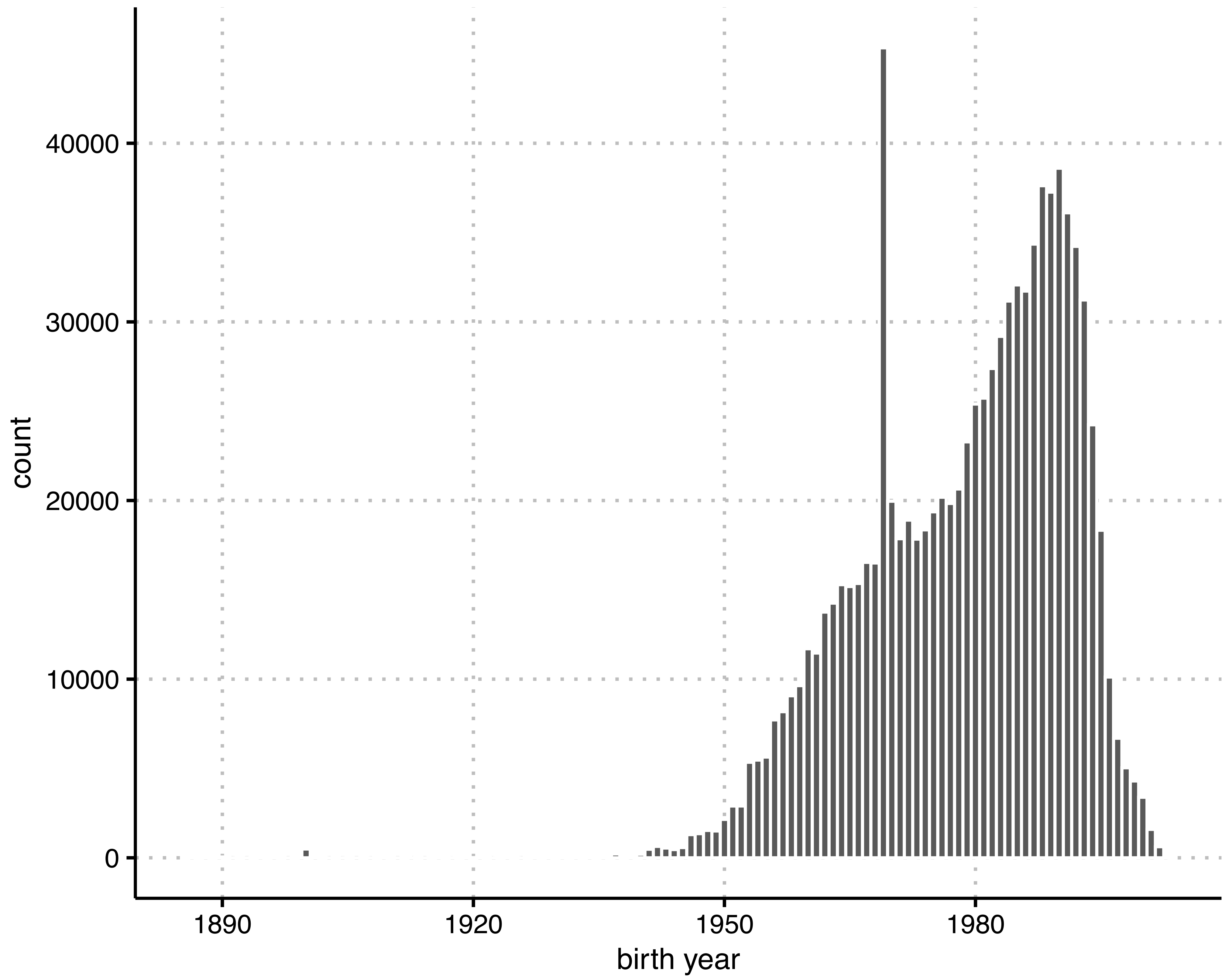
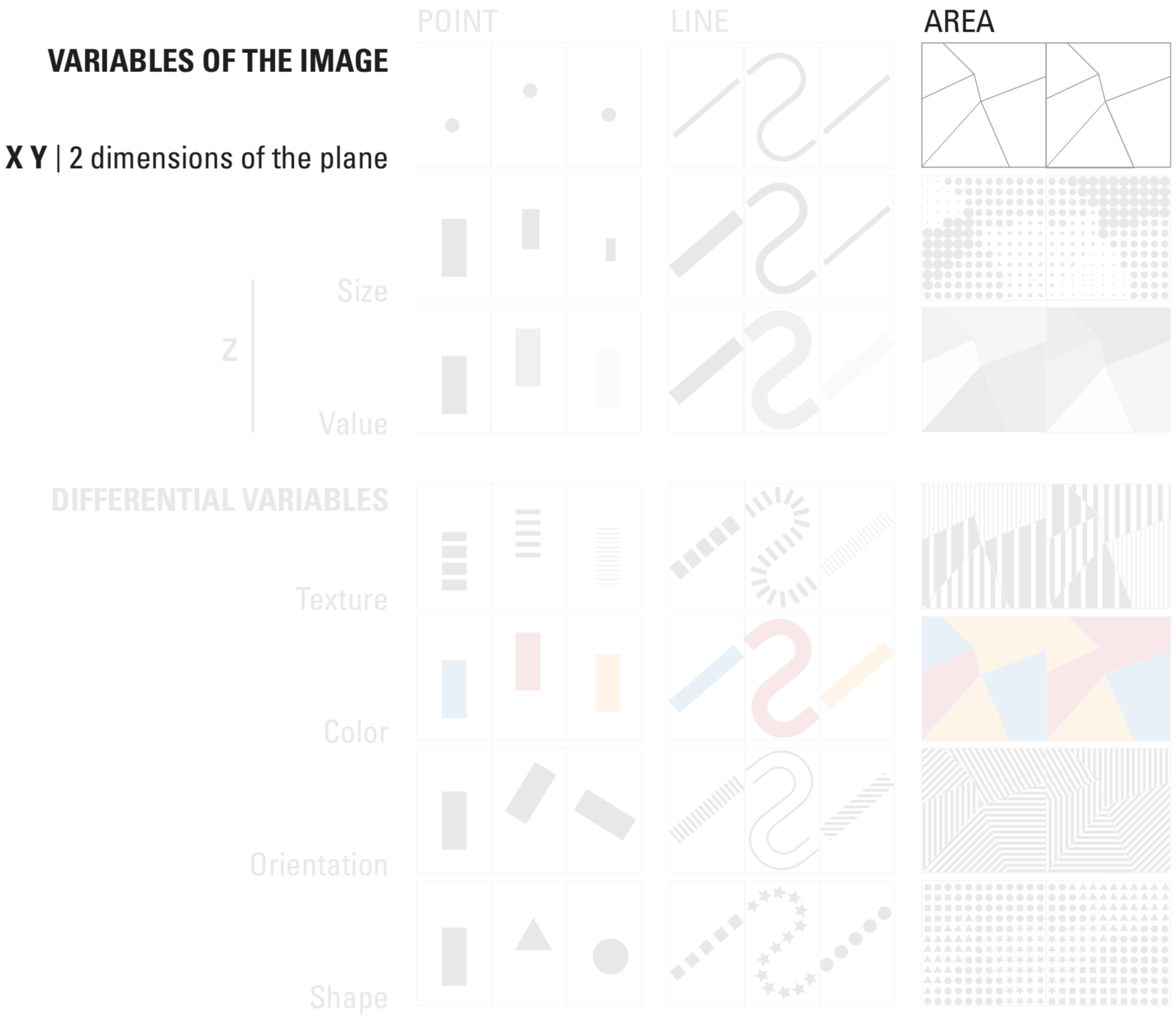




data encodings, visual channels for encoding data



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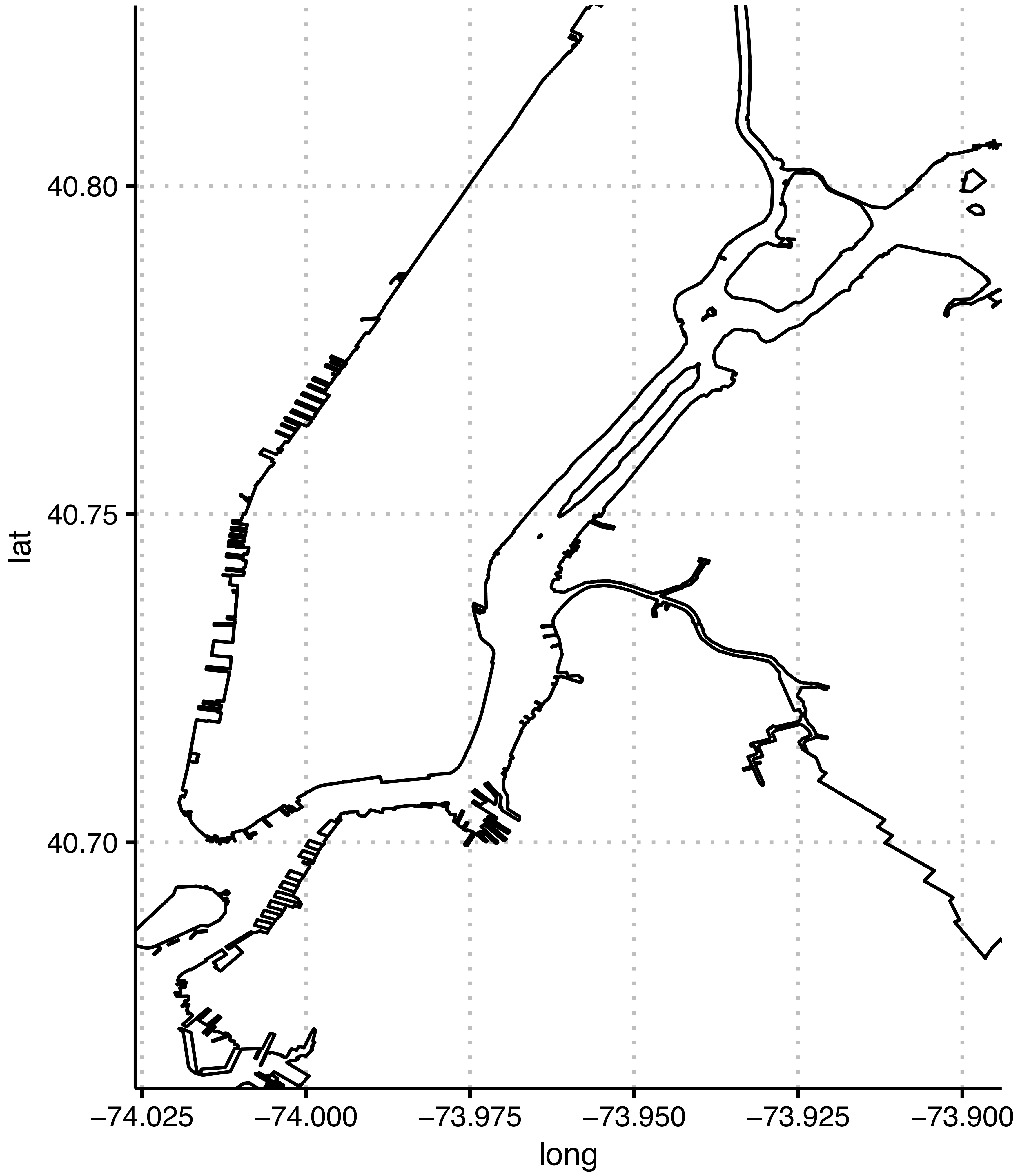

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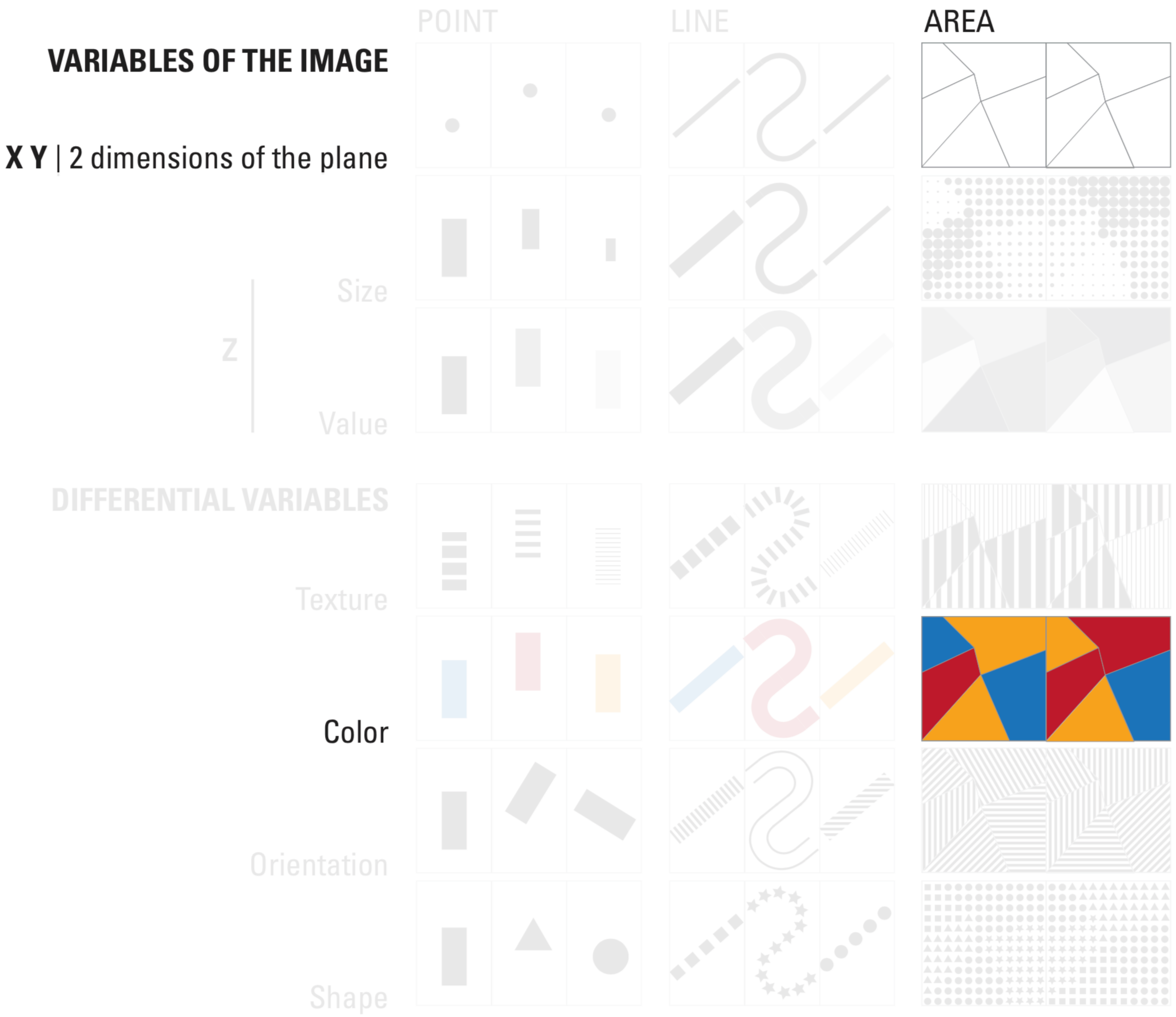

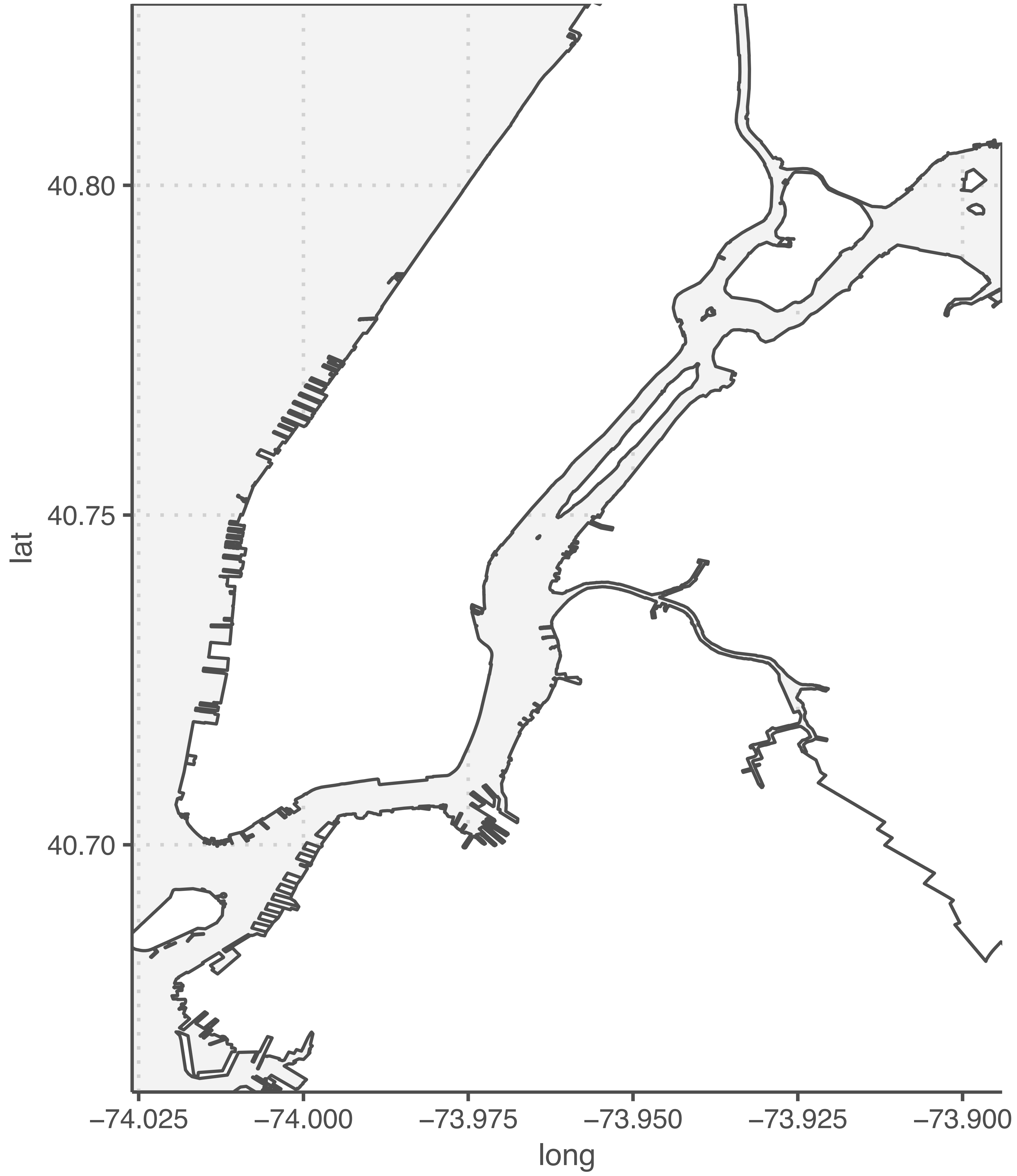

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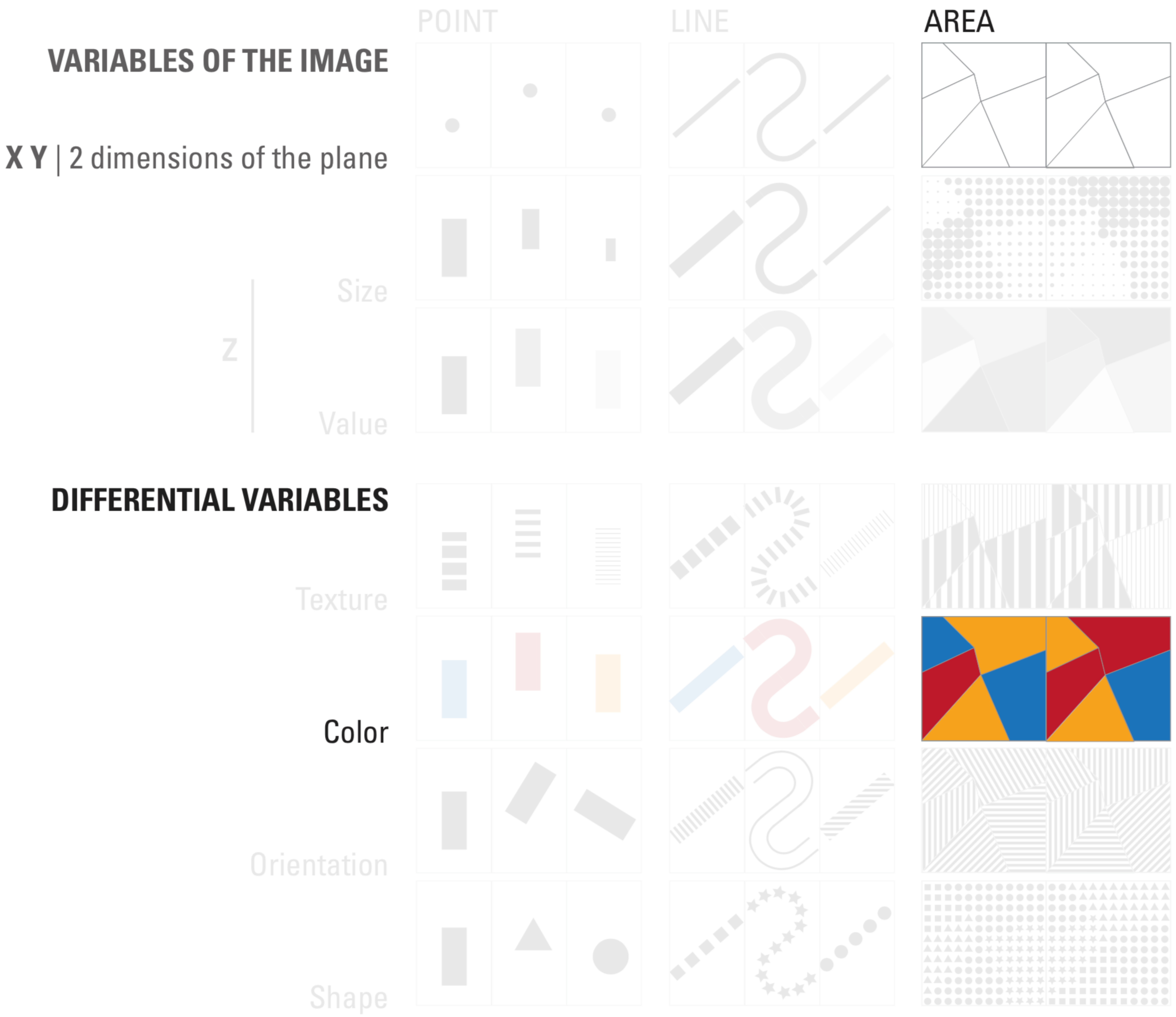
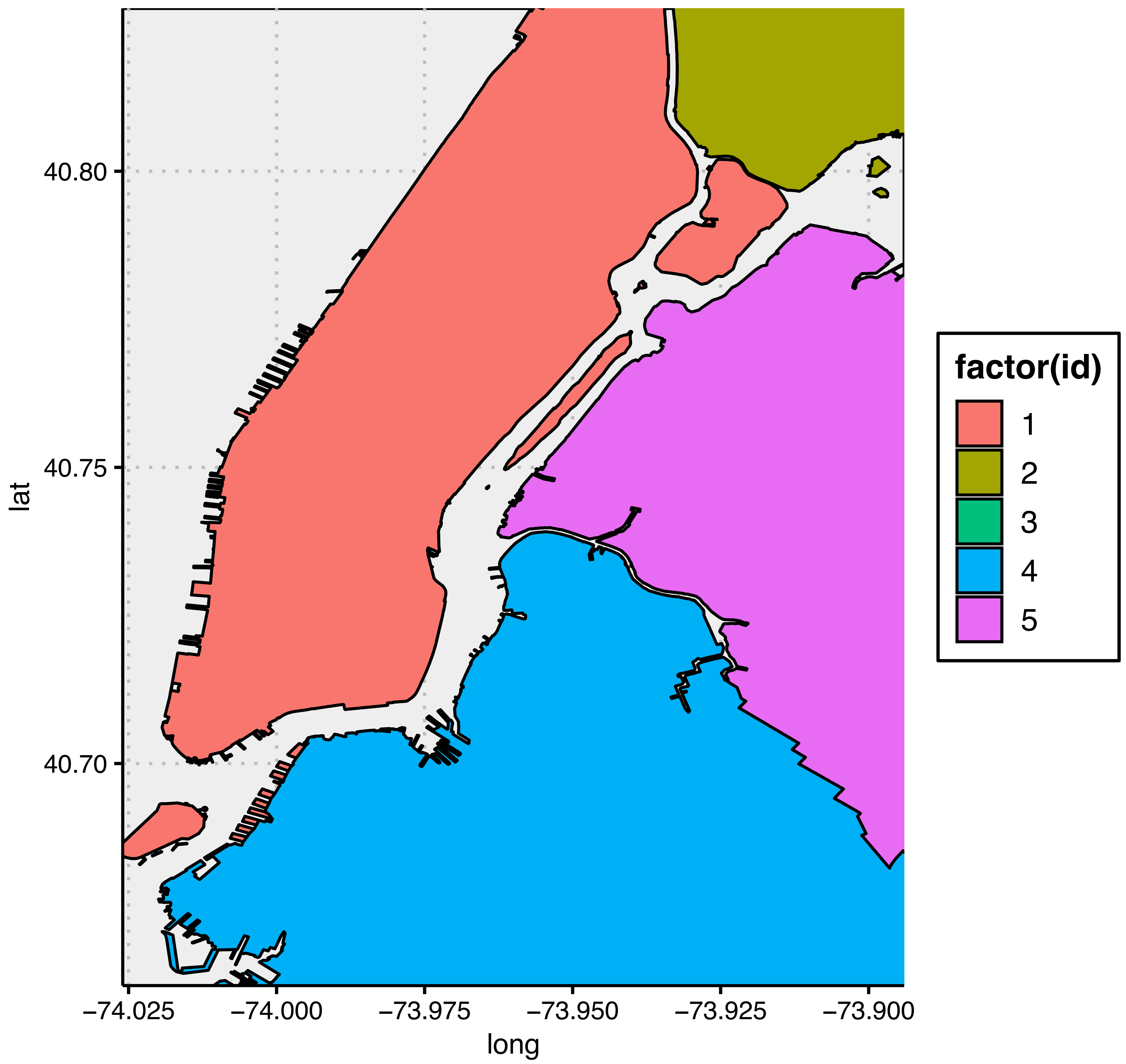
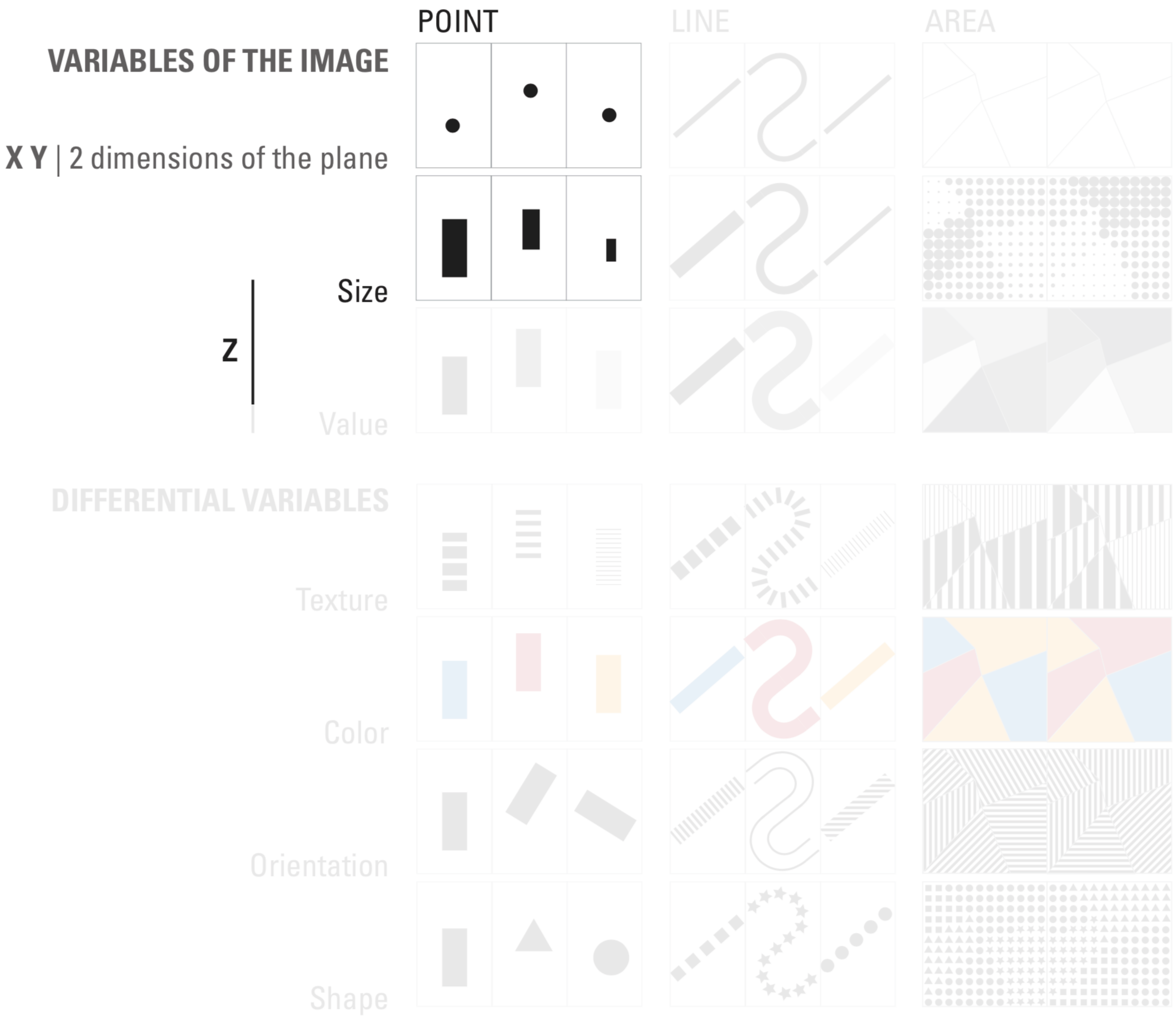




data encodings, visual channels for encoding data



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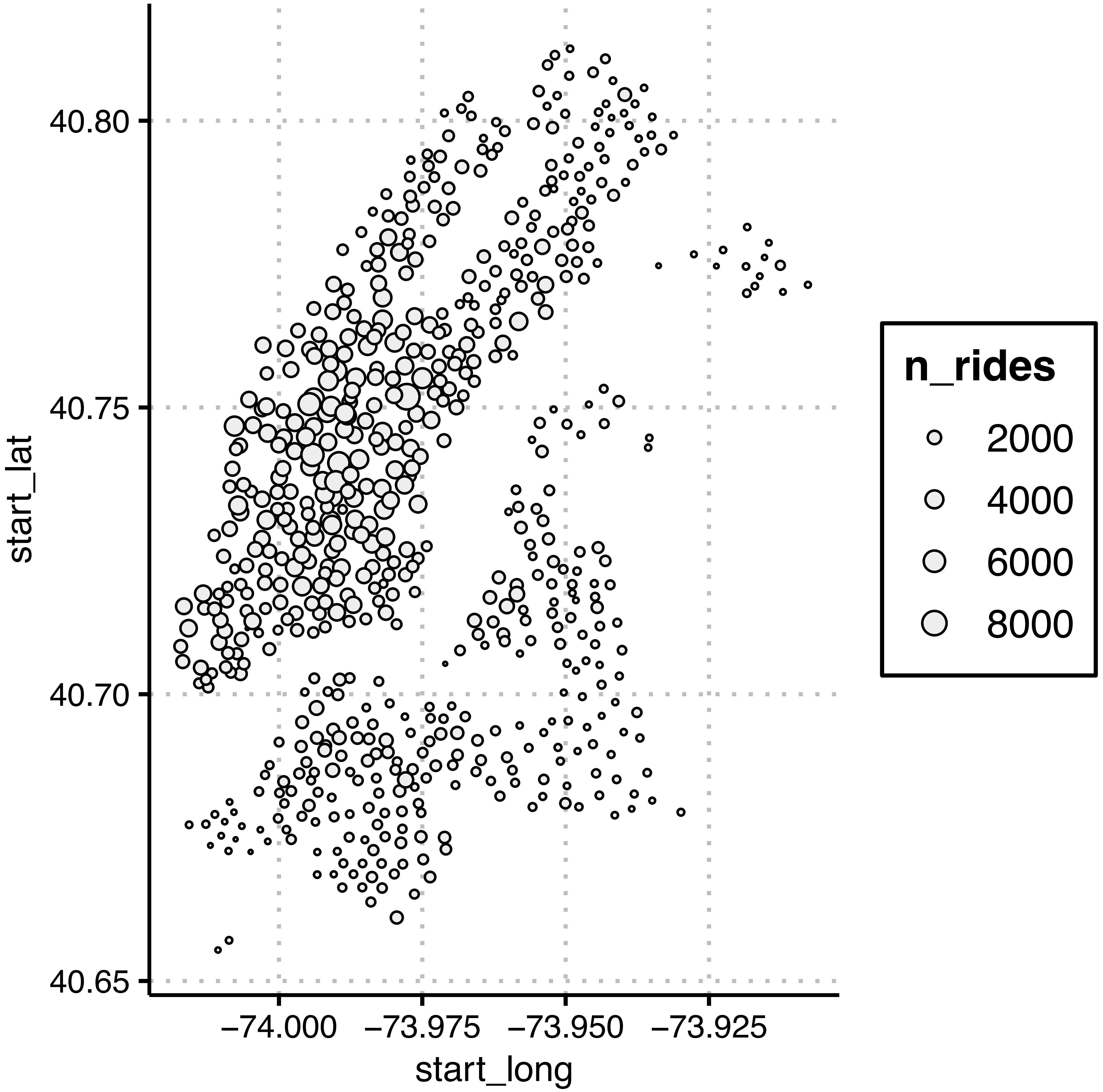

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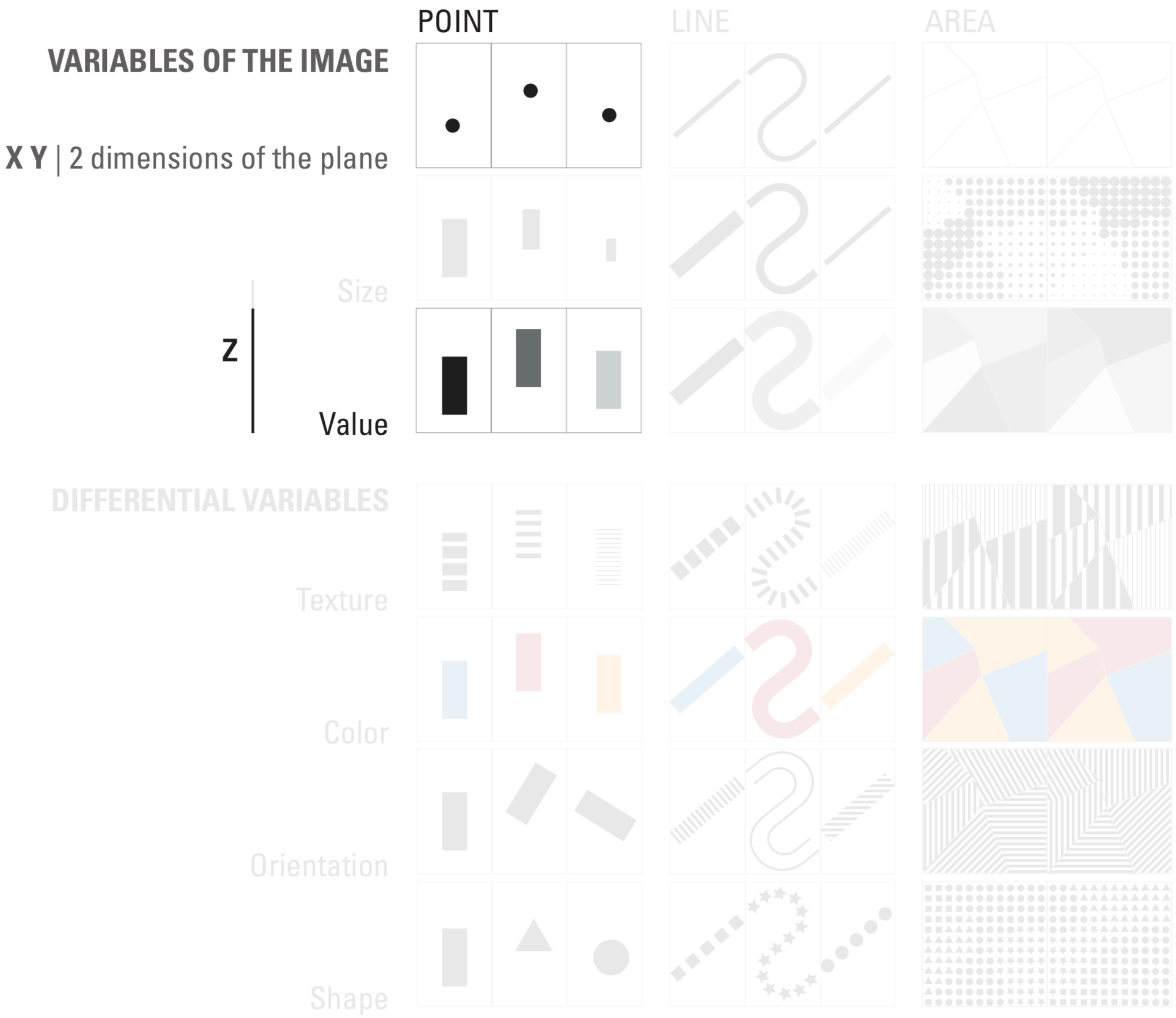

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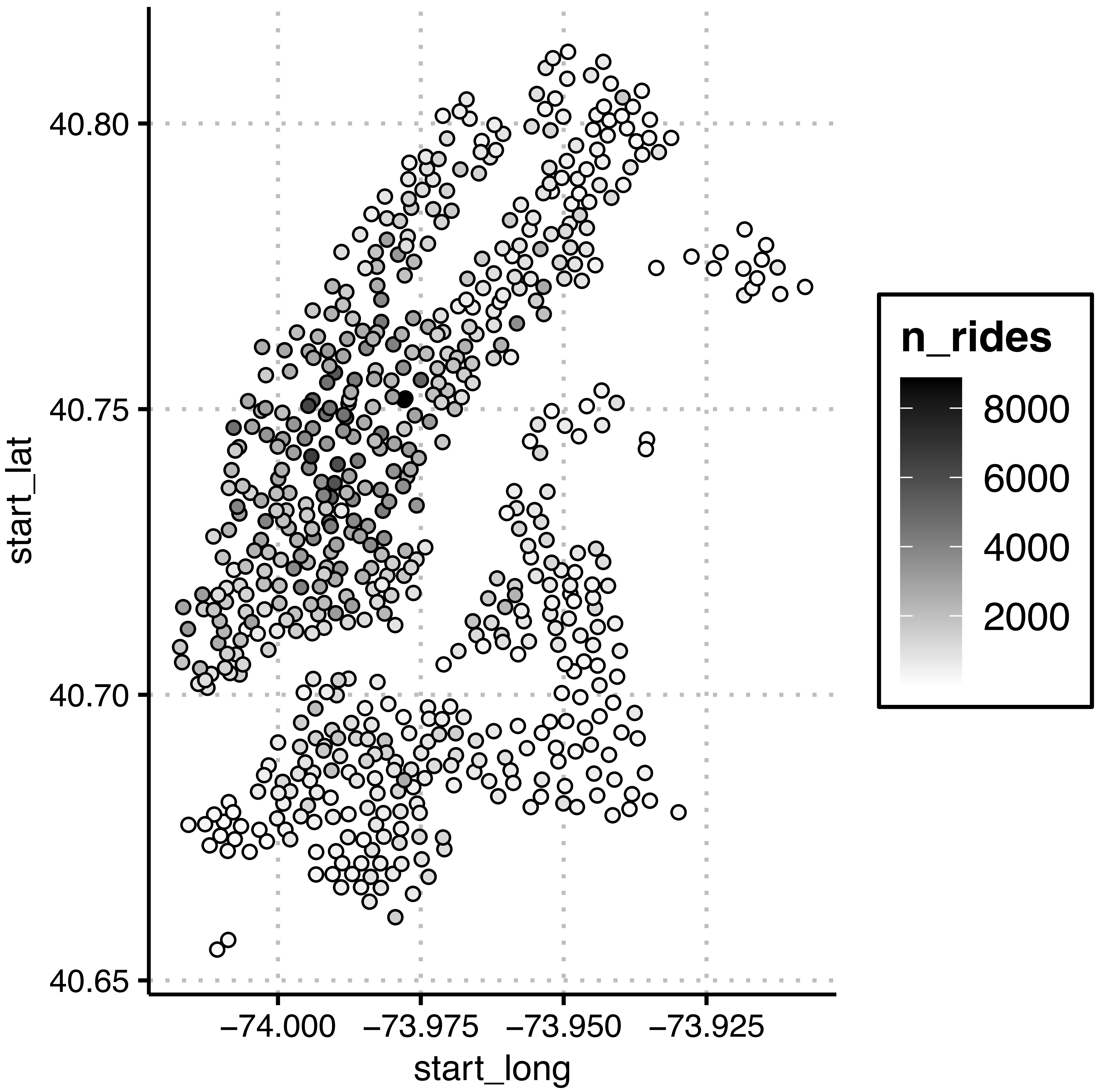

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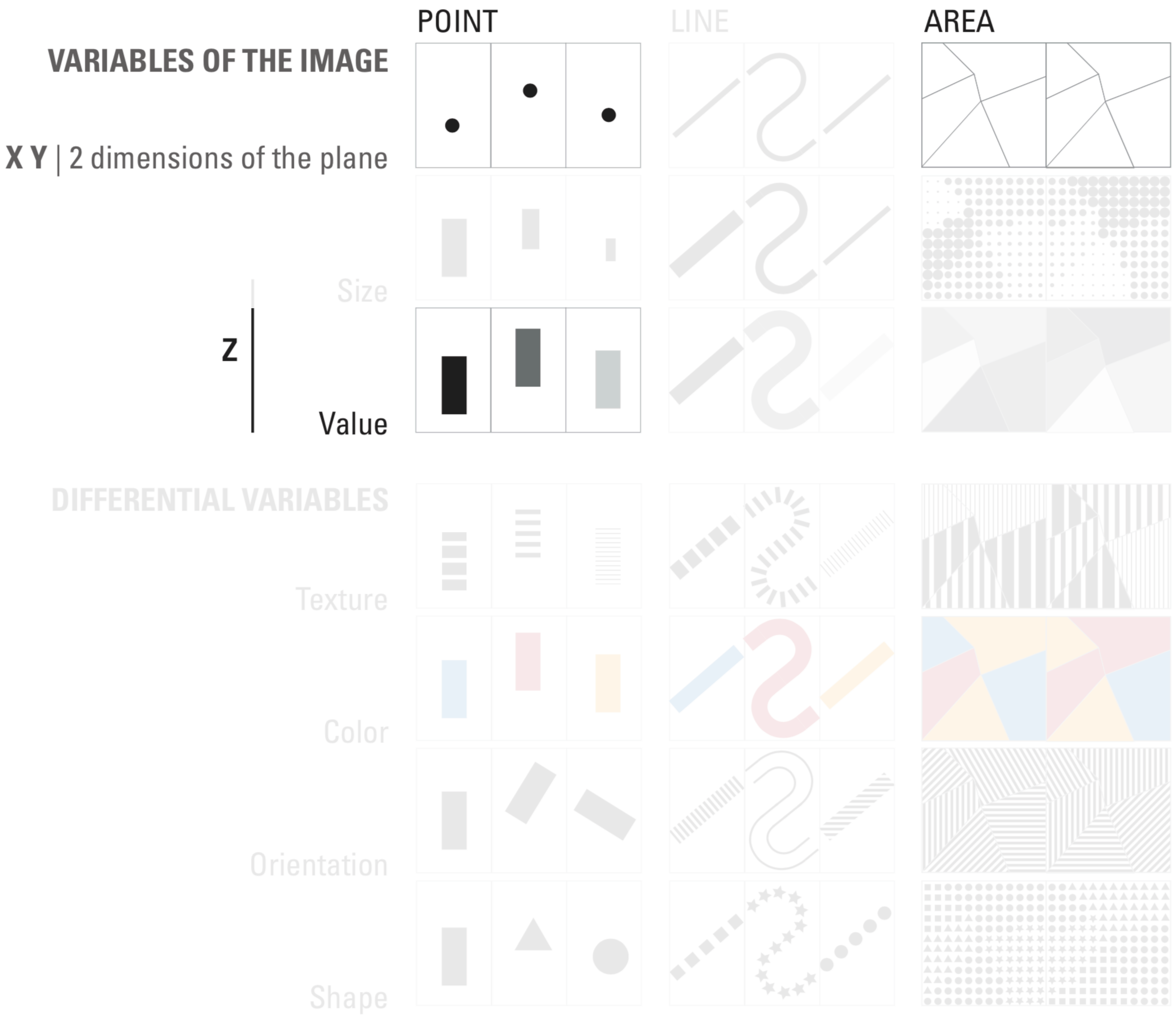

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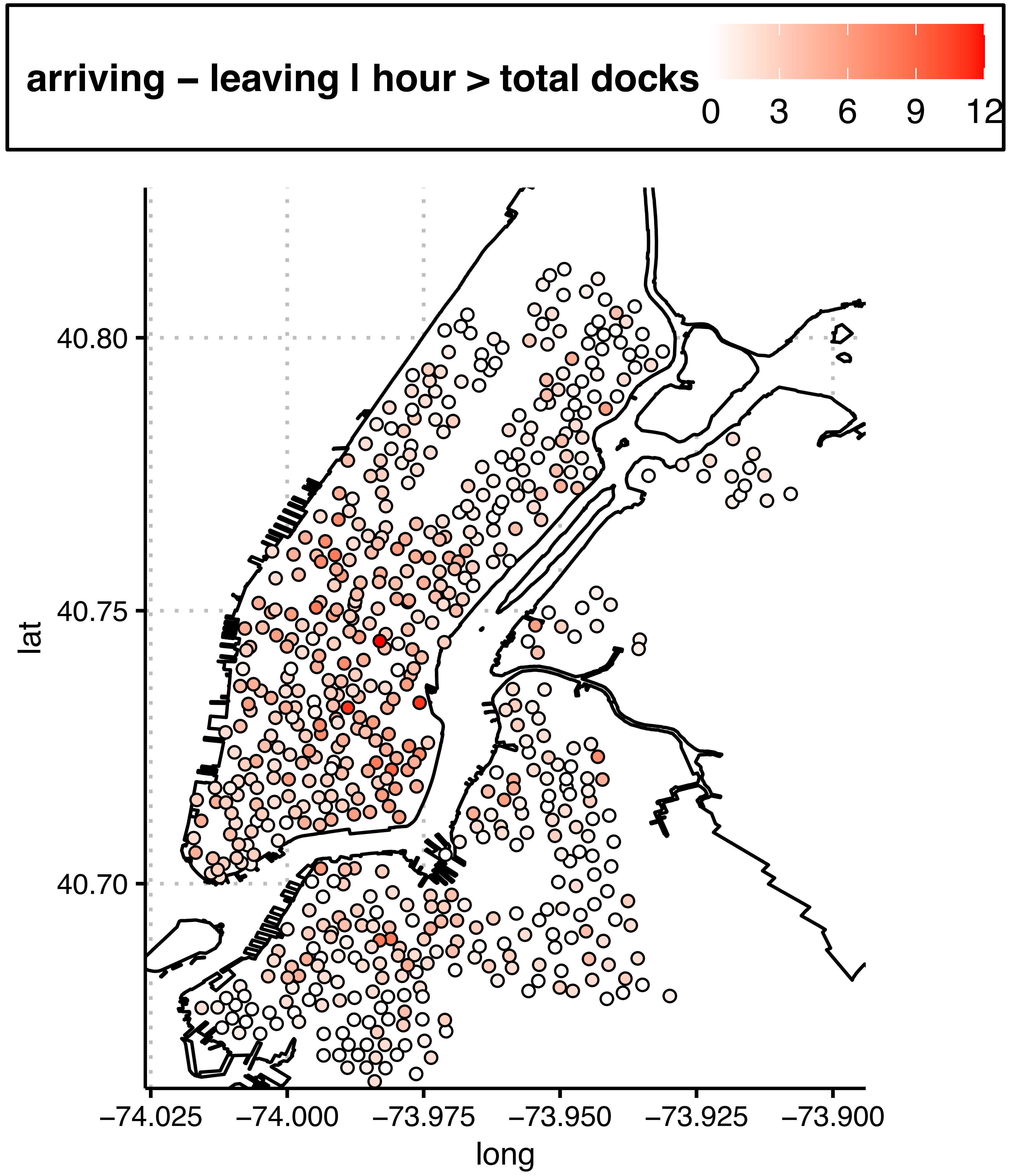

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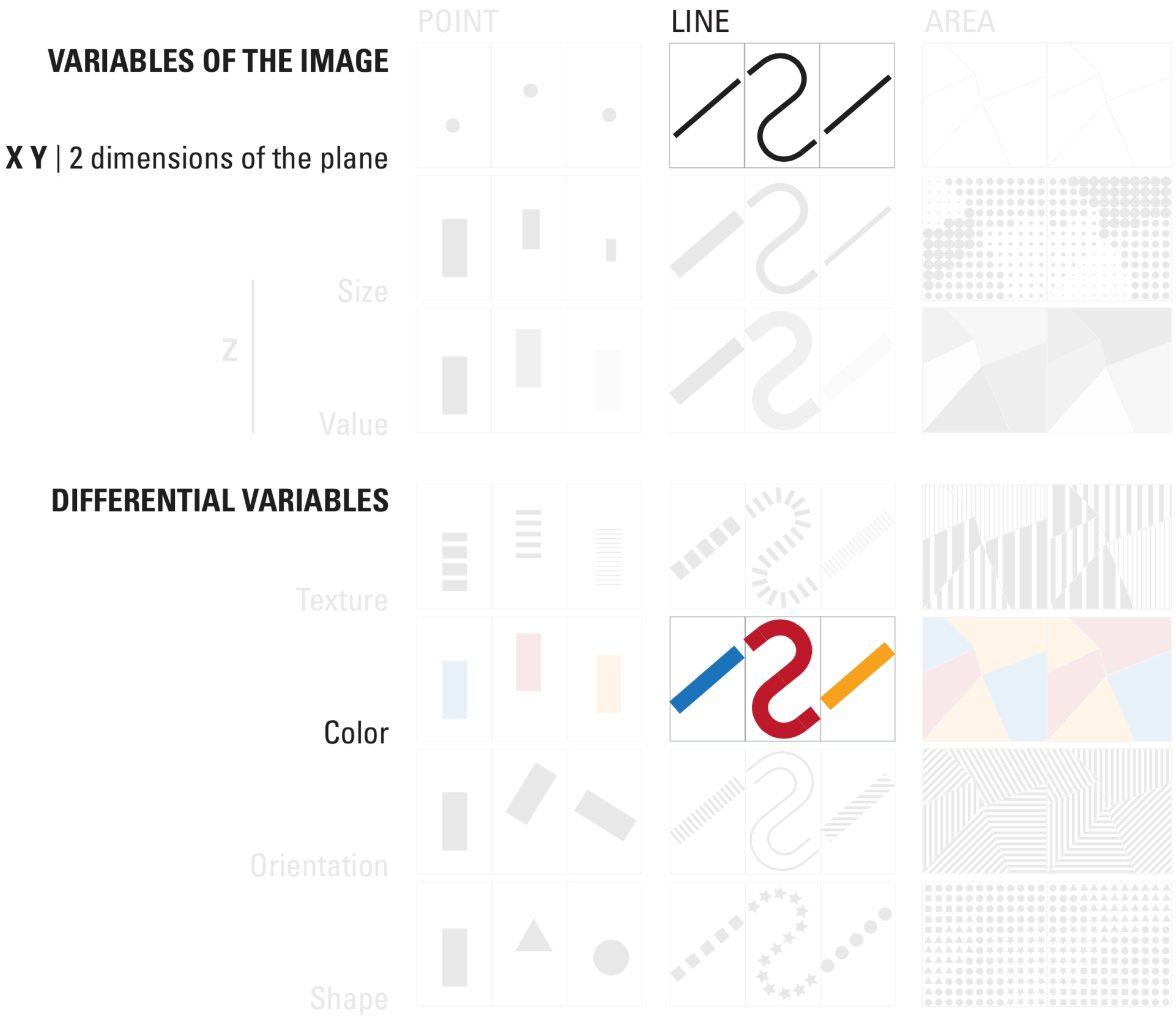

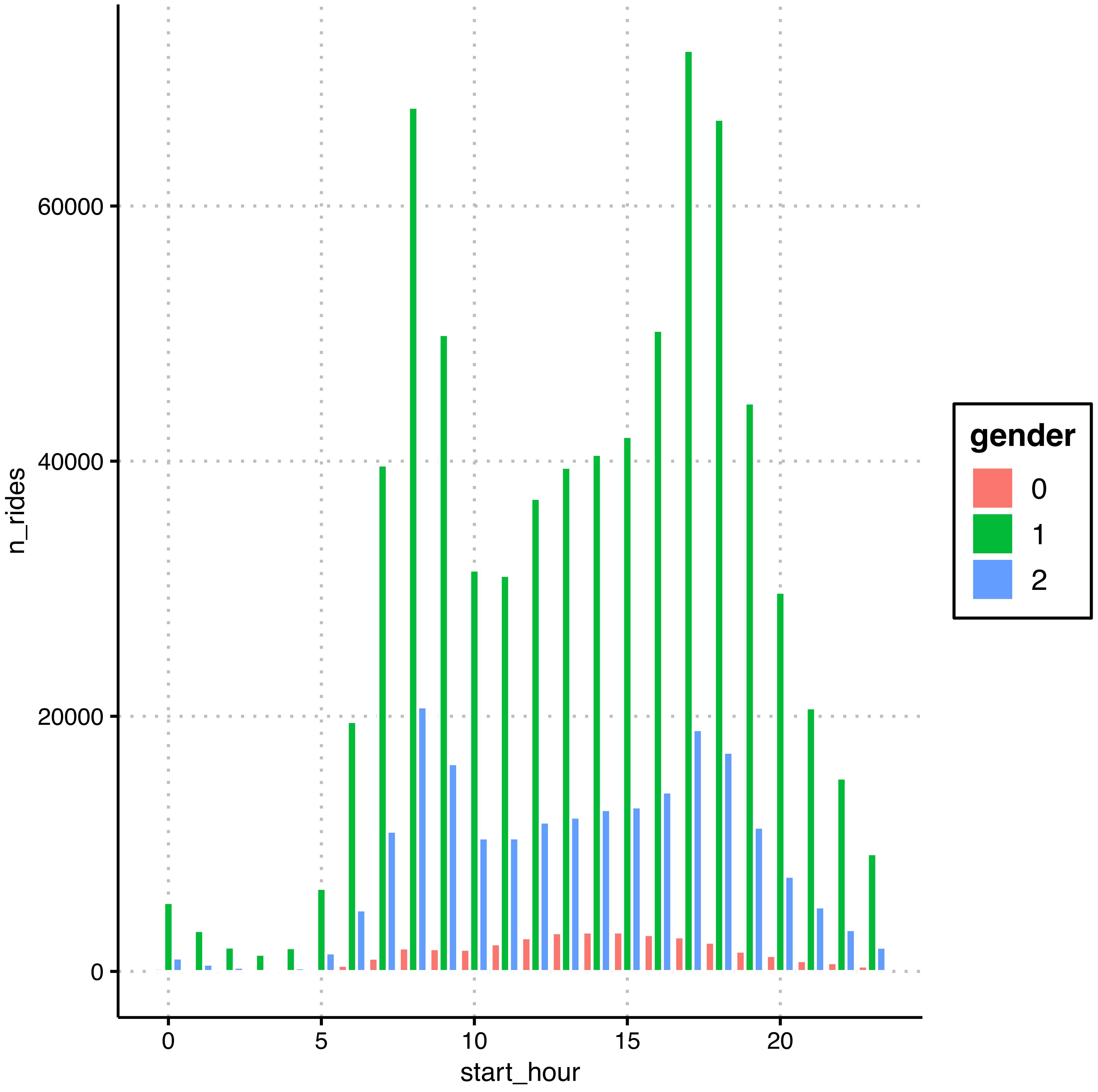

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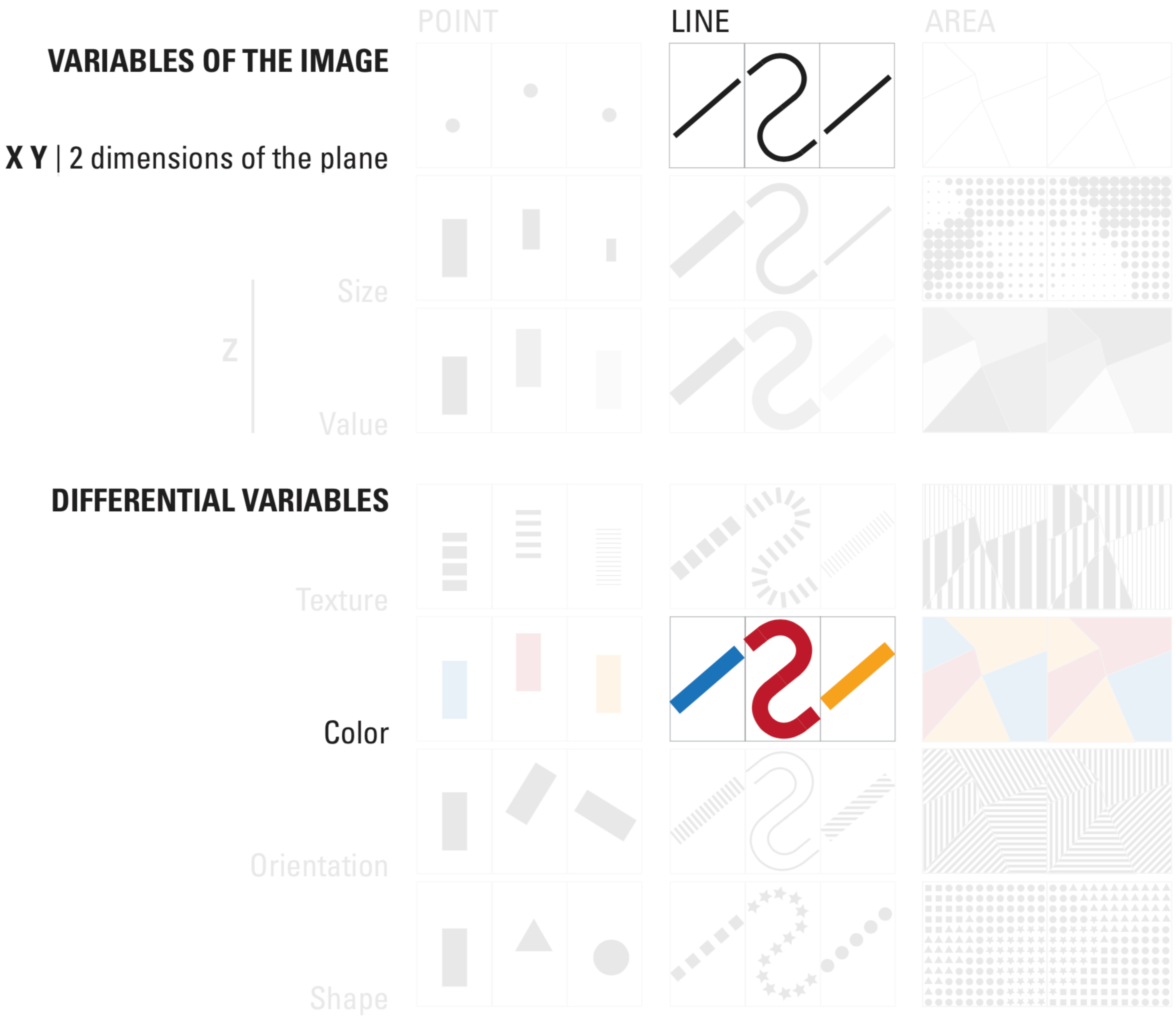
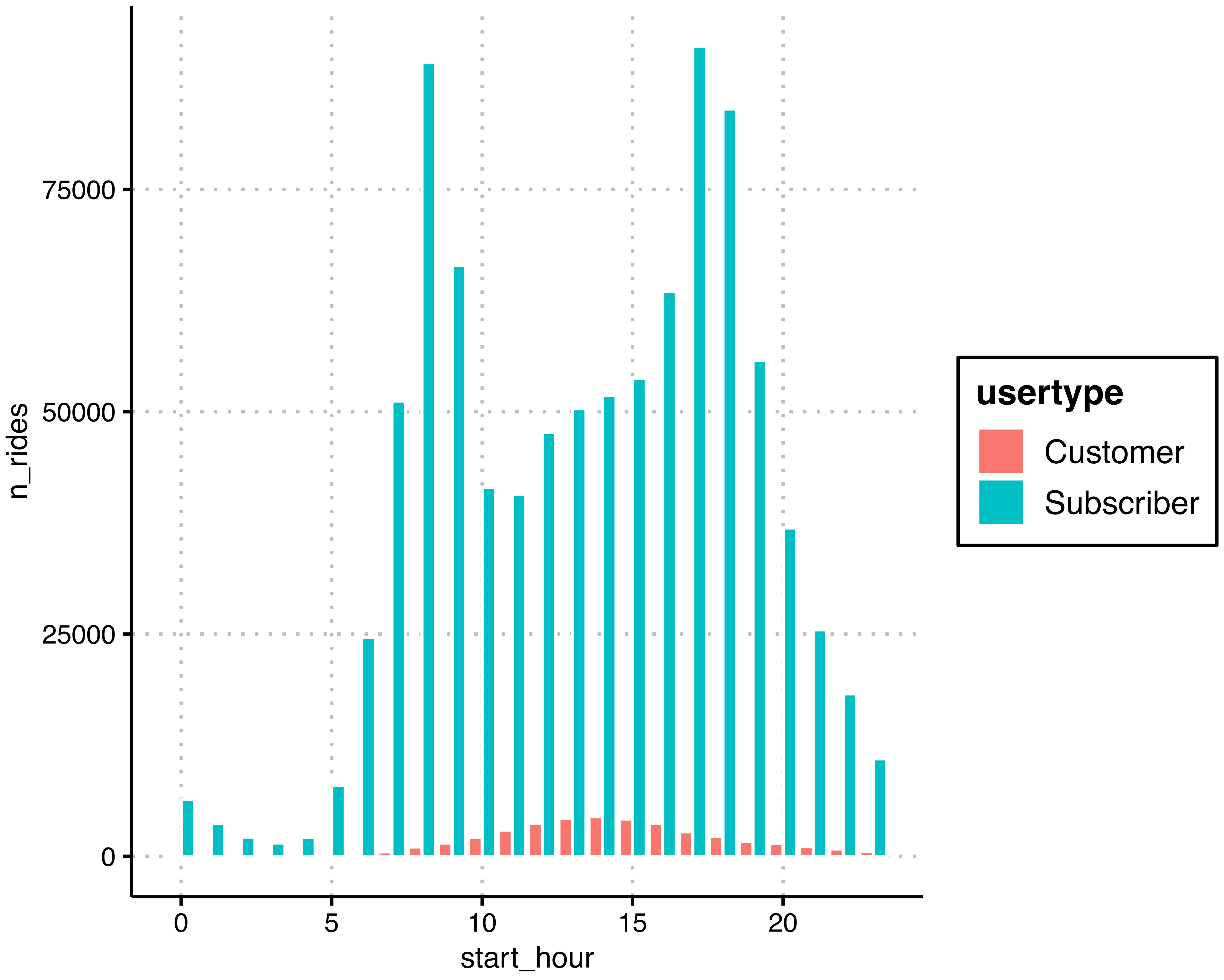
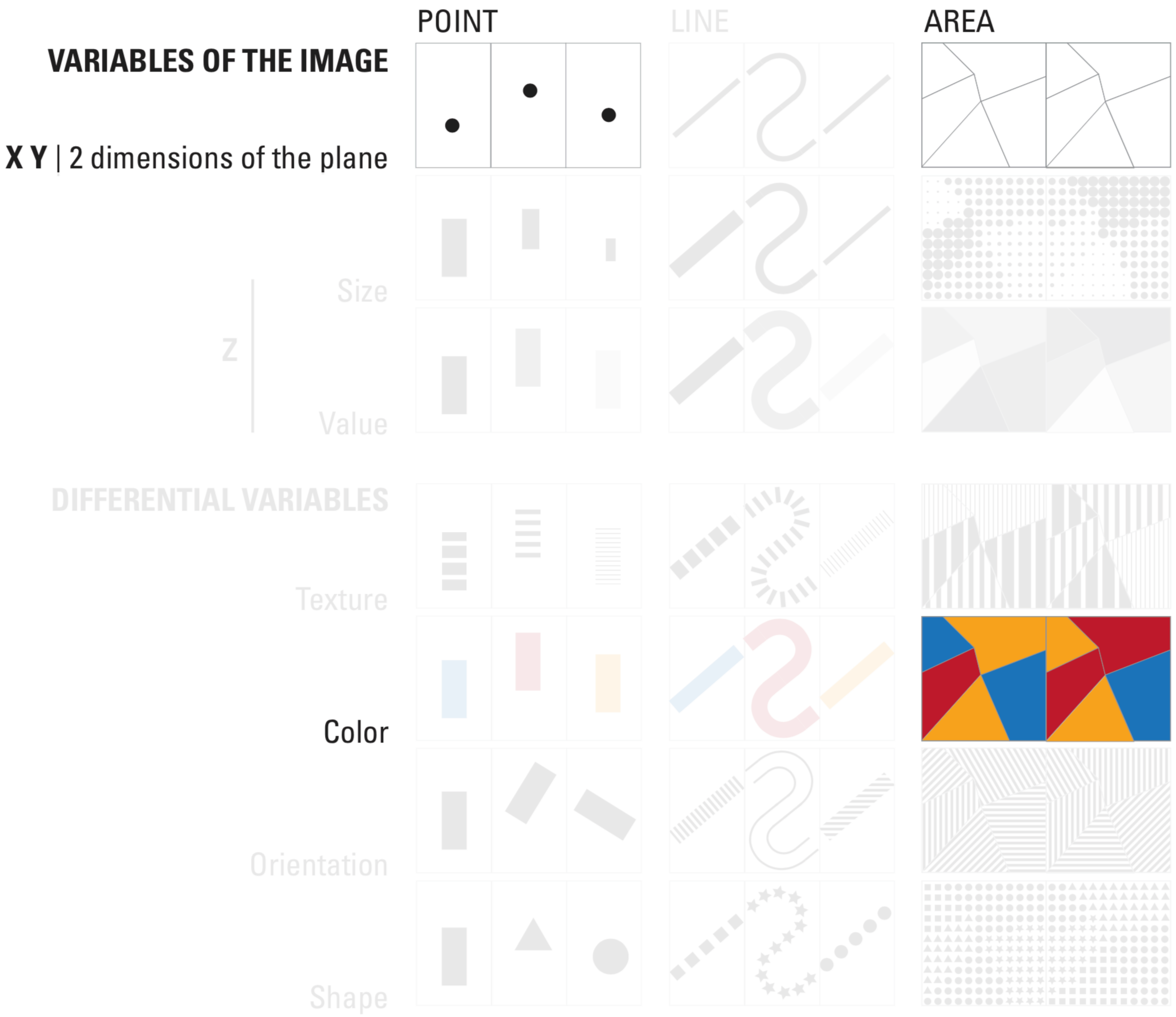


Citi Bike example — *exploratory data analysis*





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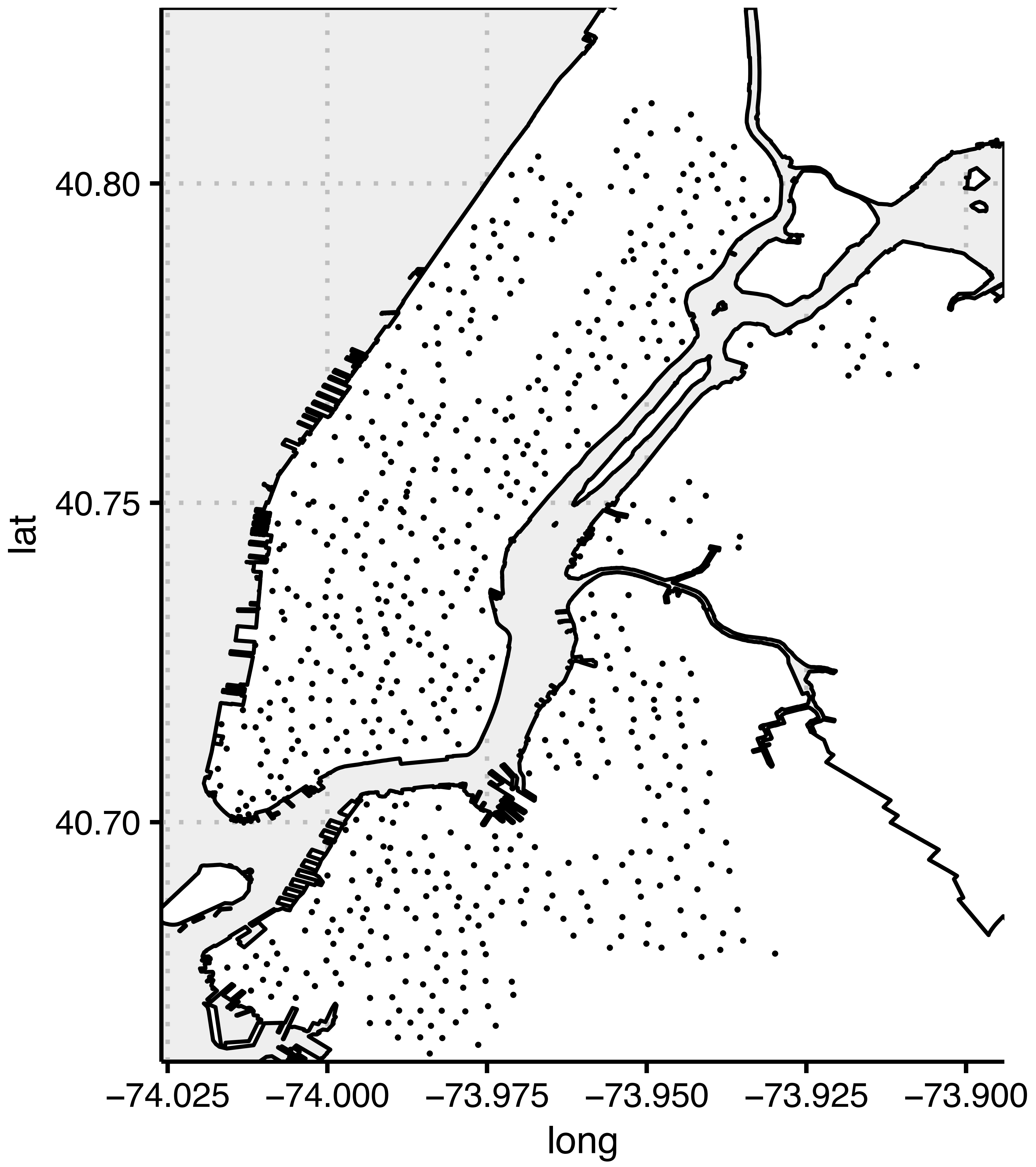

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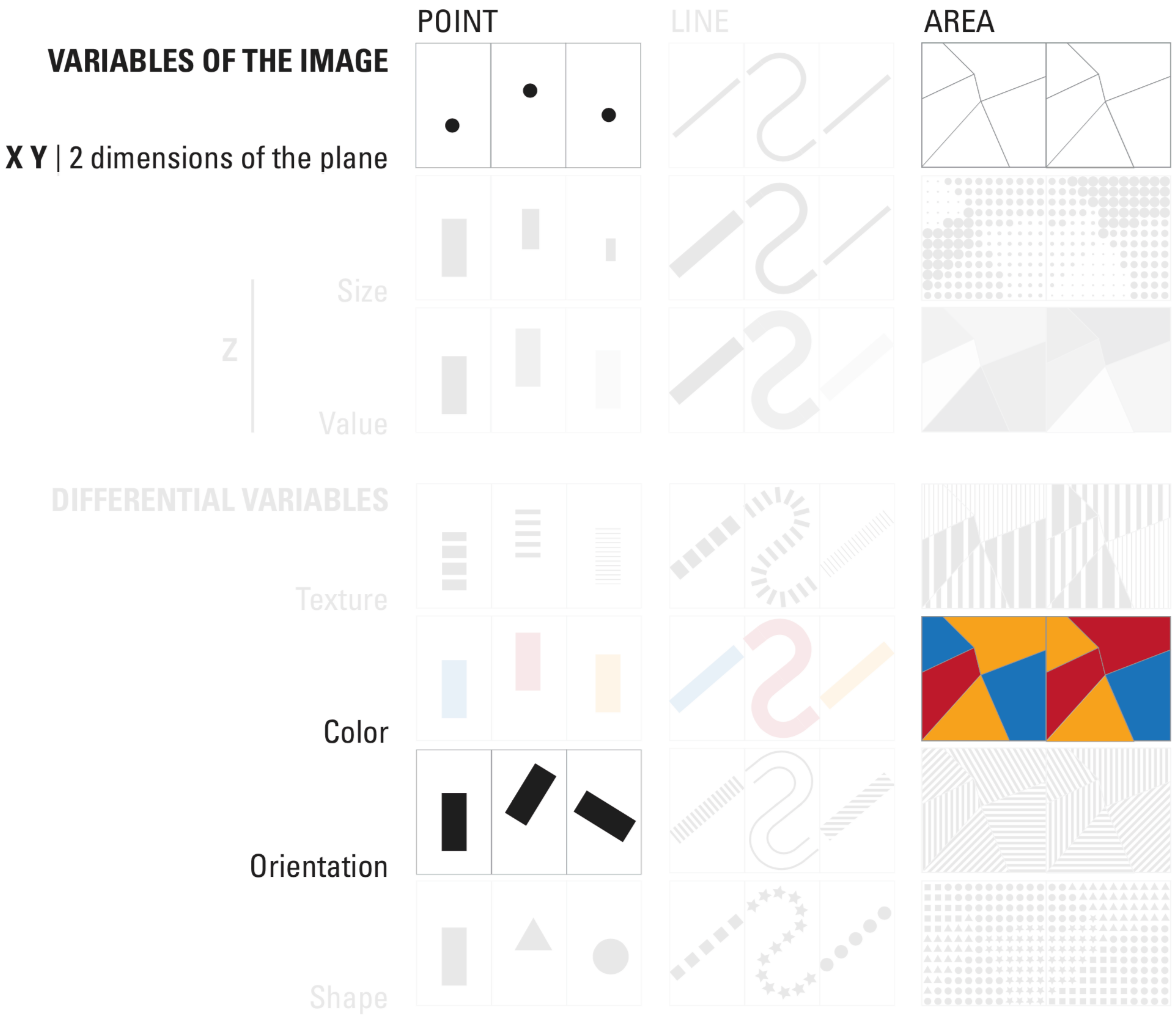

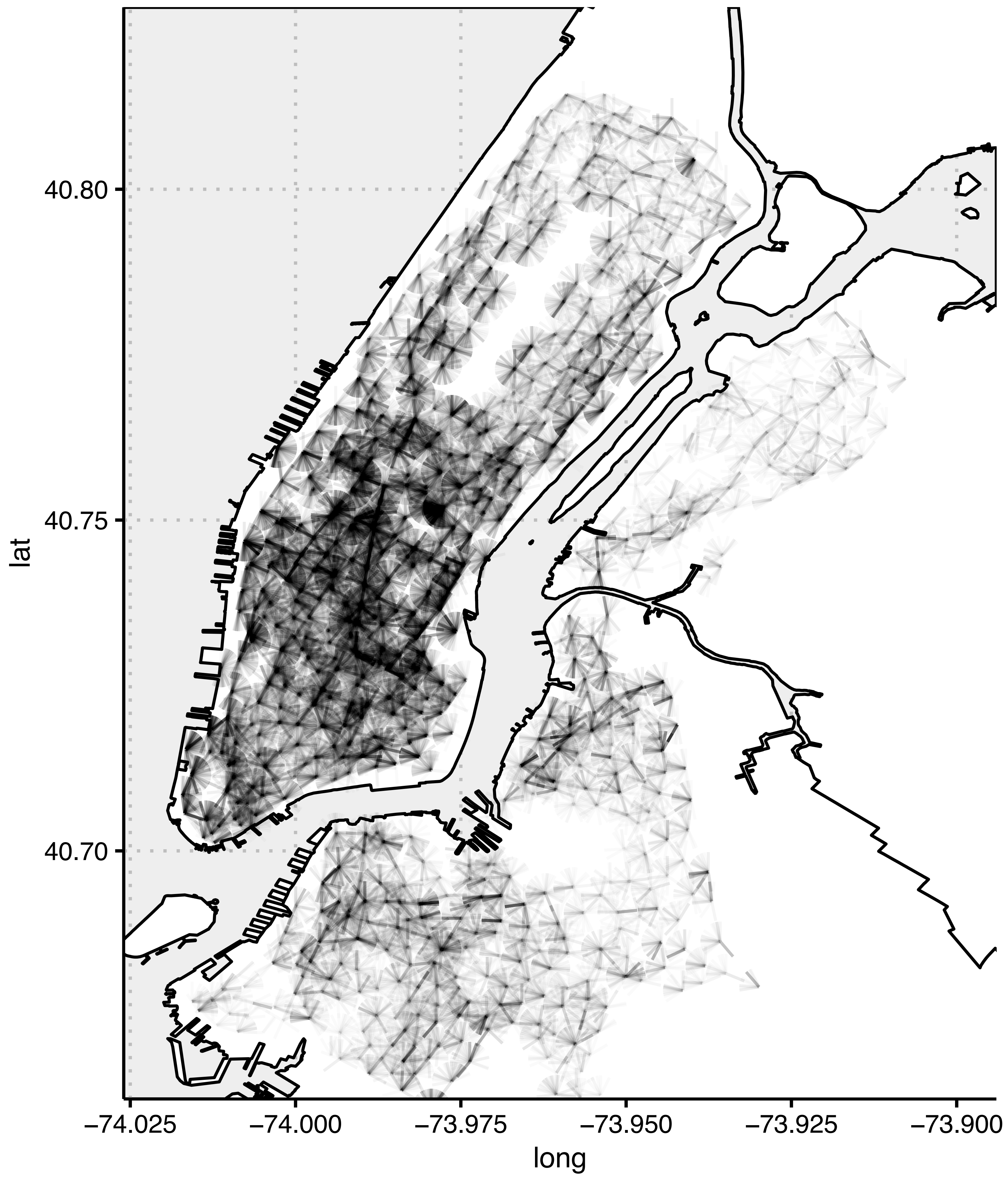

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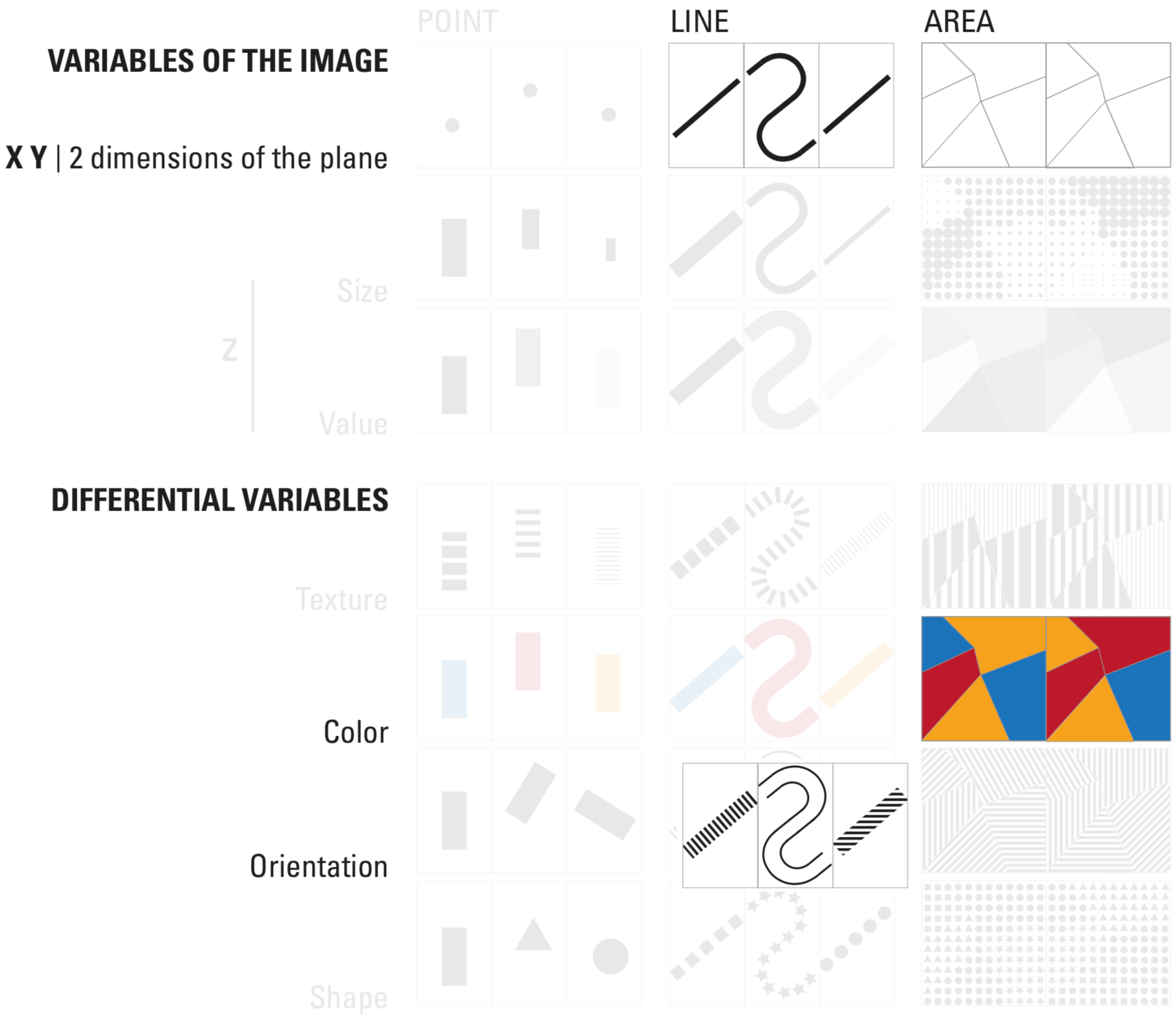
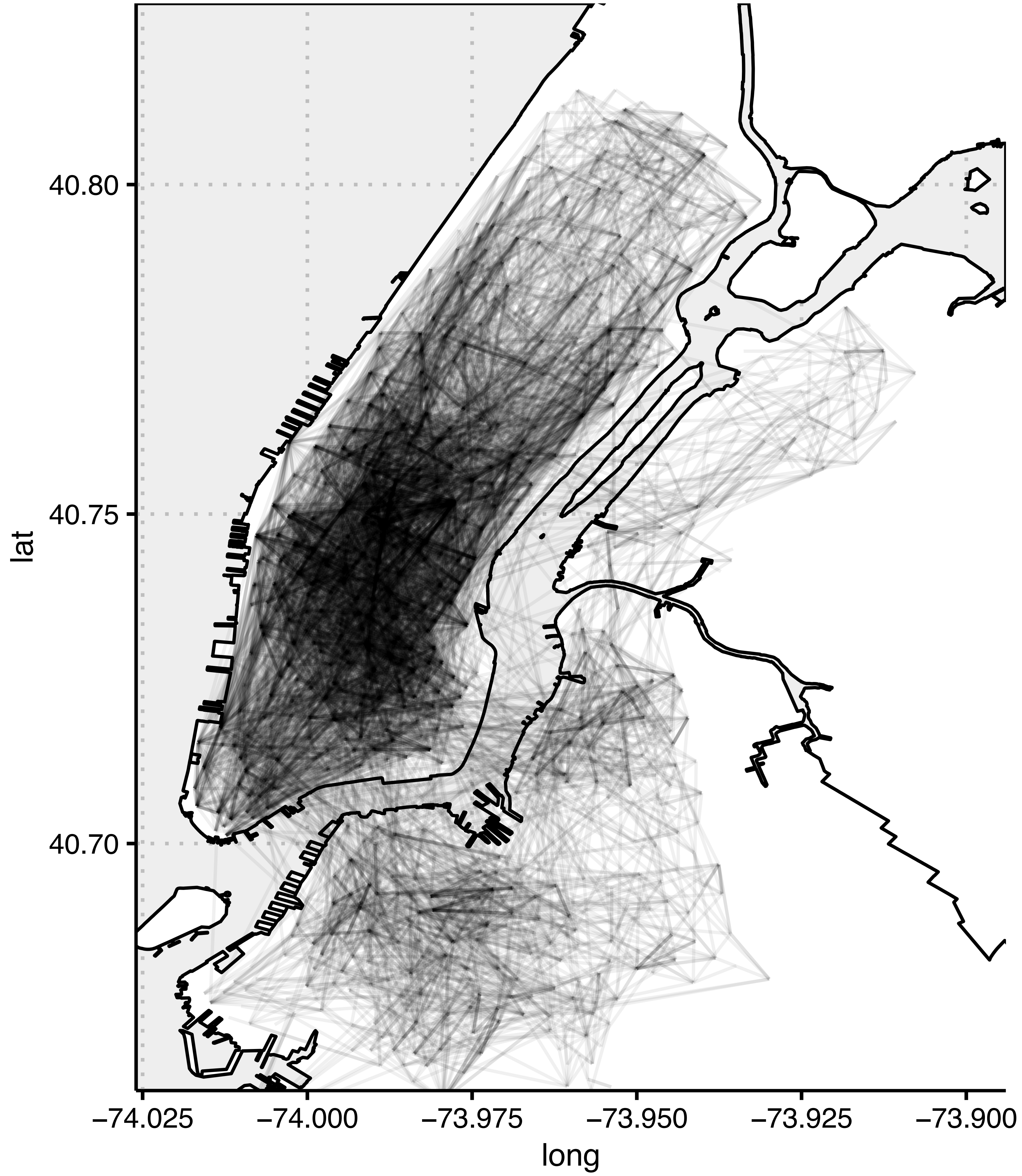
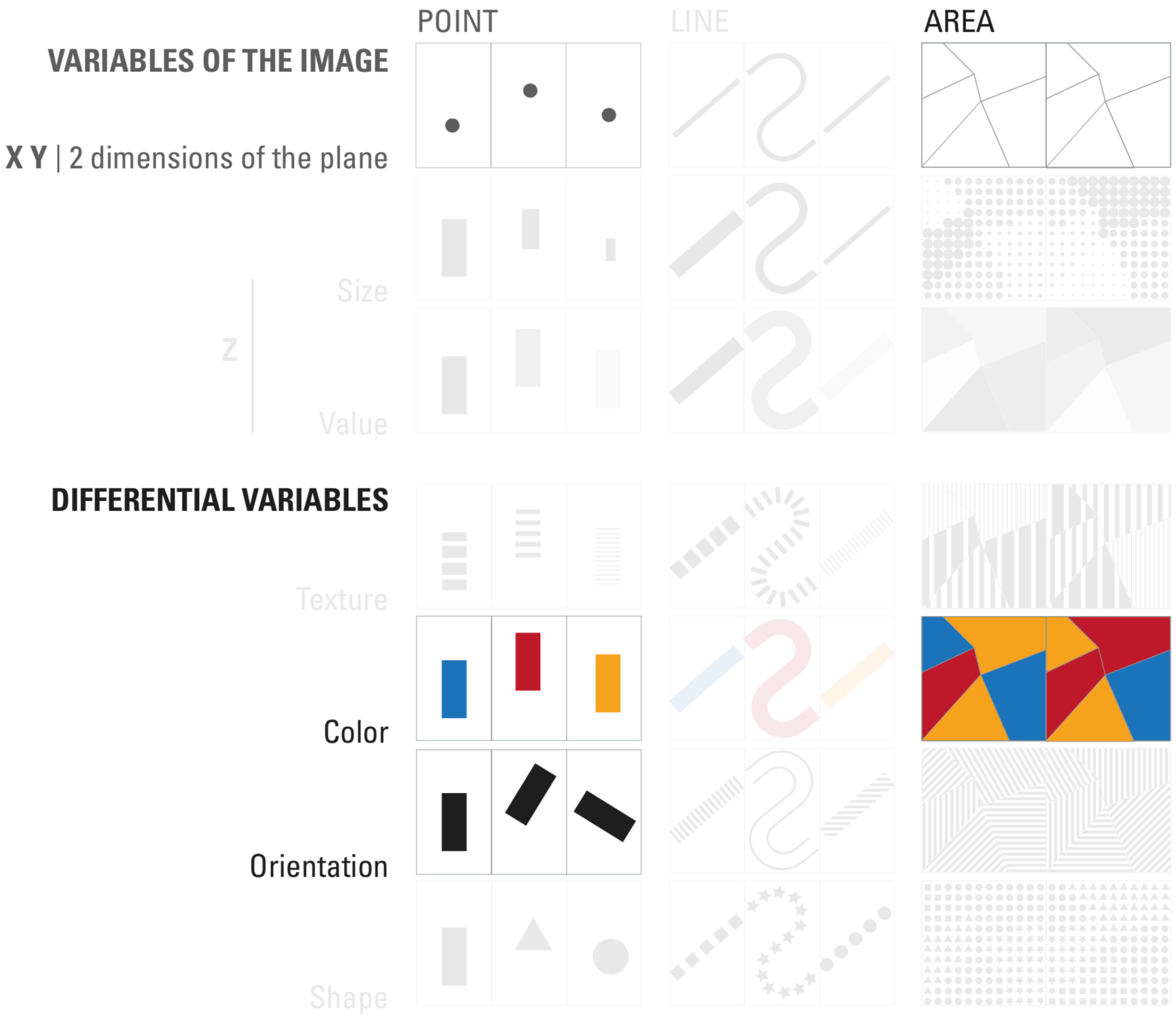
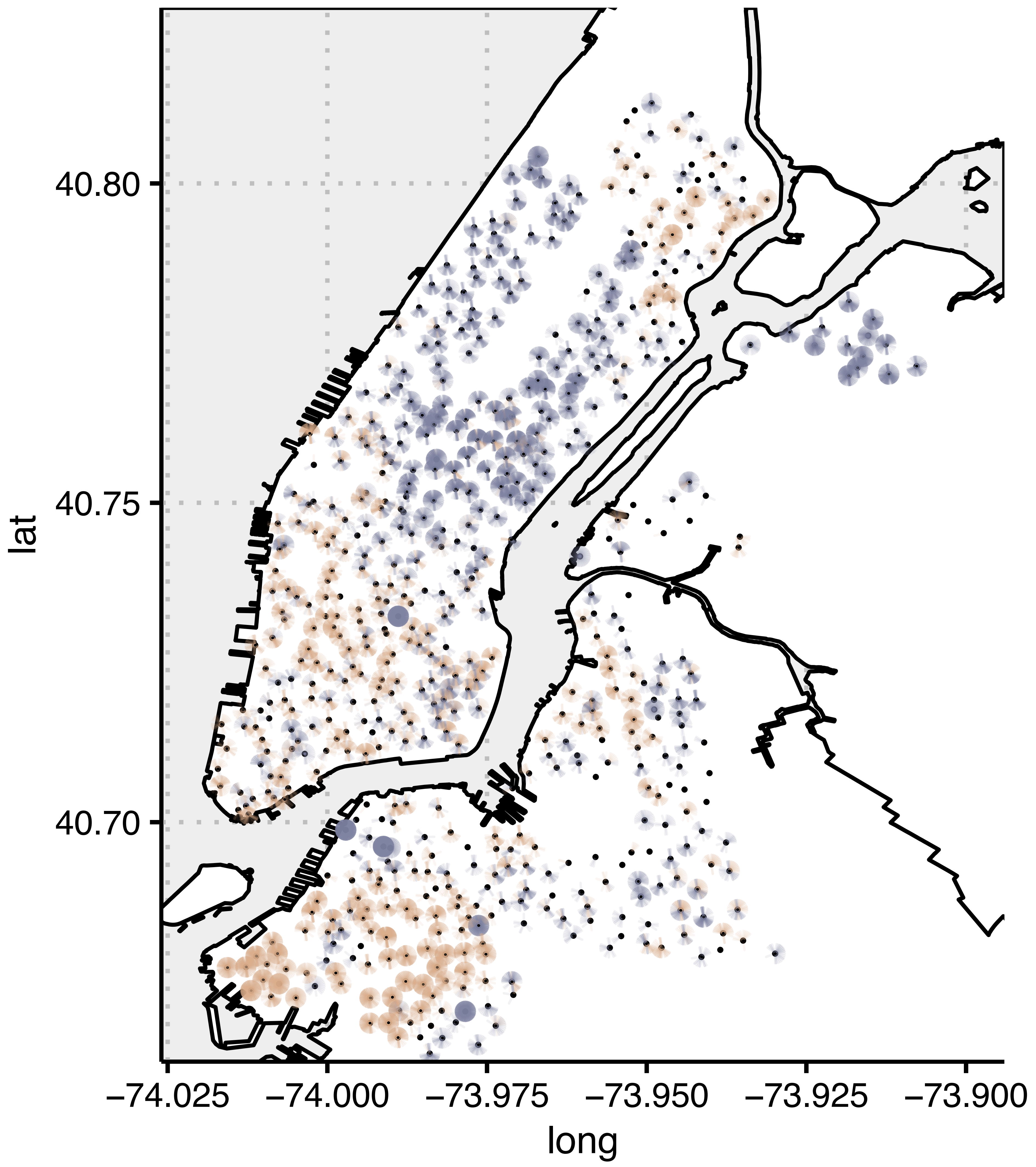




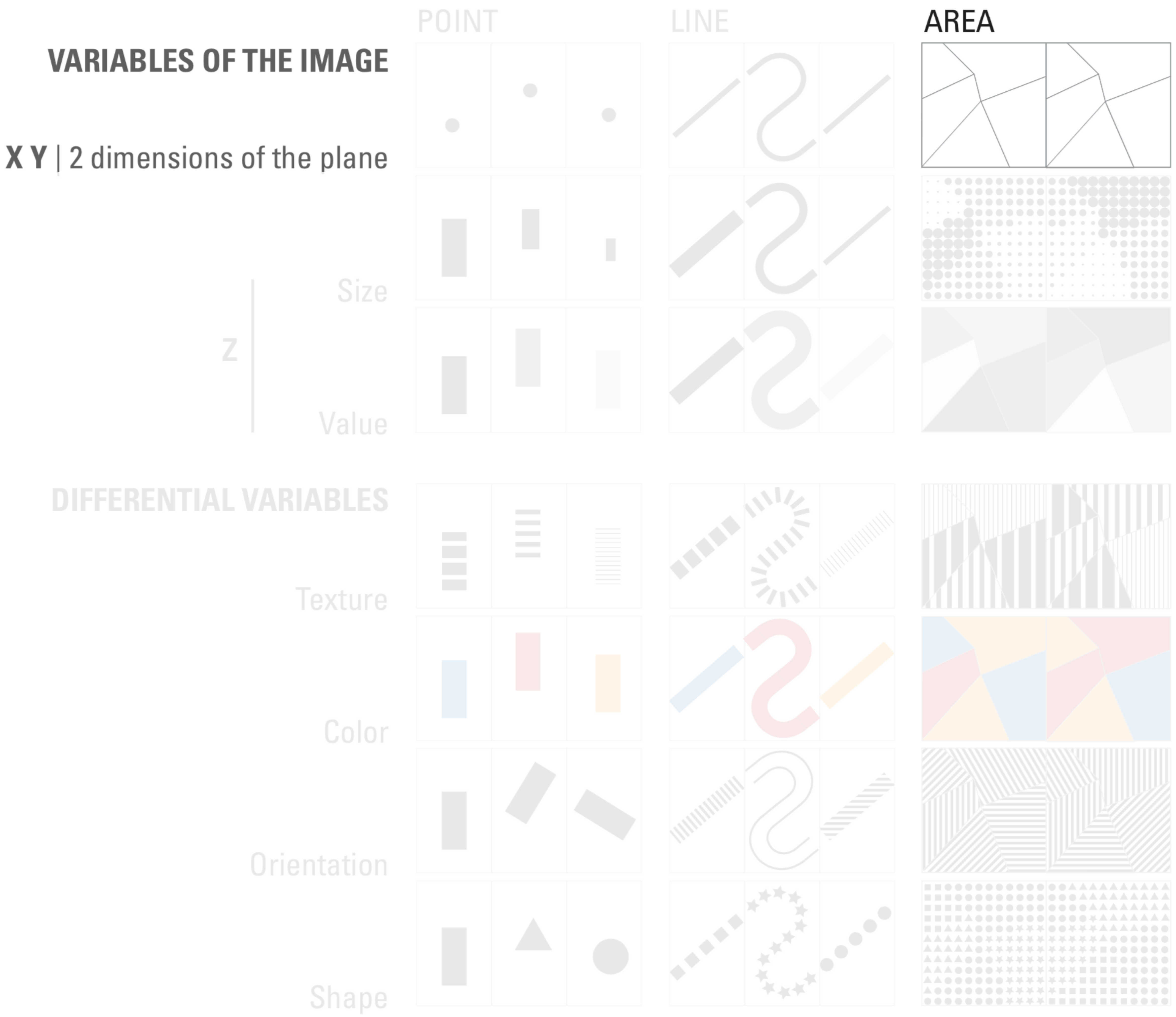
 visual channels for encoding data

Citi Bike example — *exploratory data analysis*

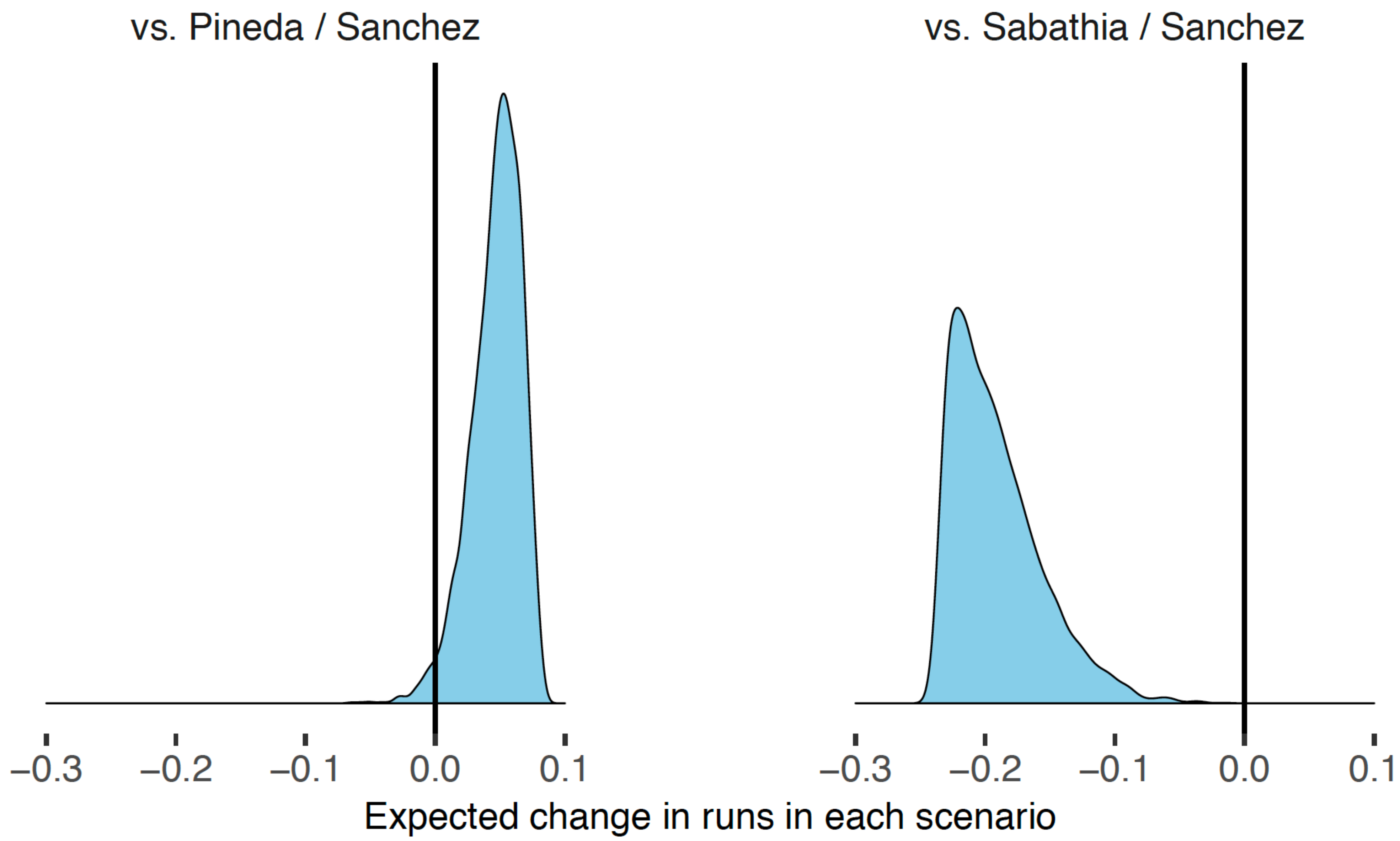




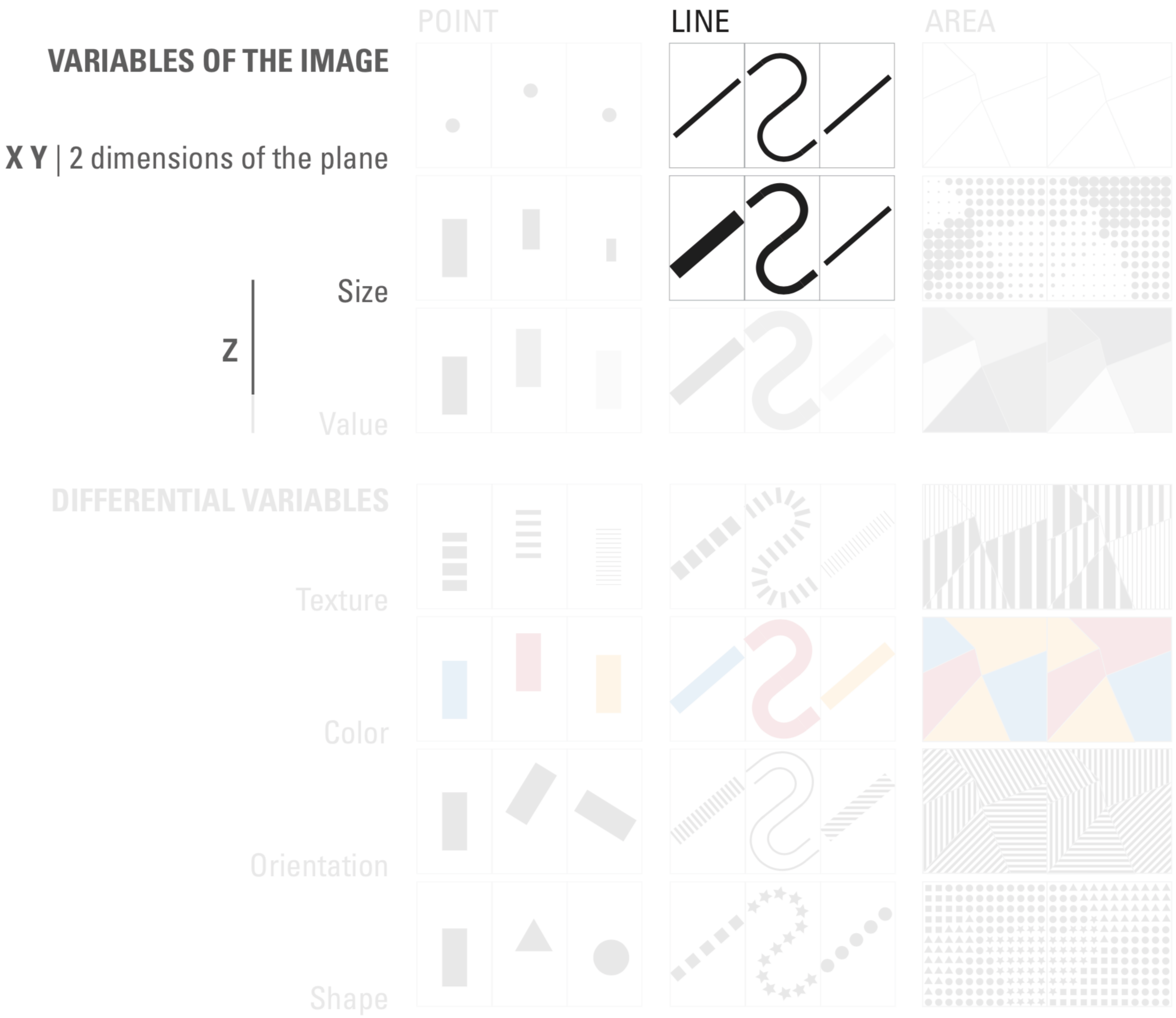
data encodings, visual channels for encoding data

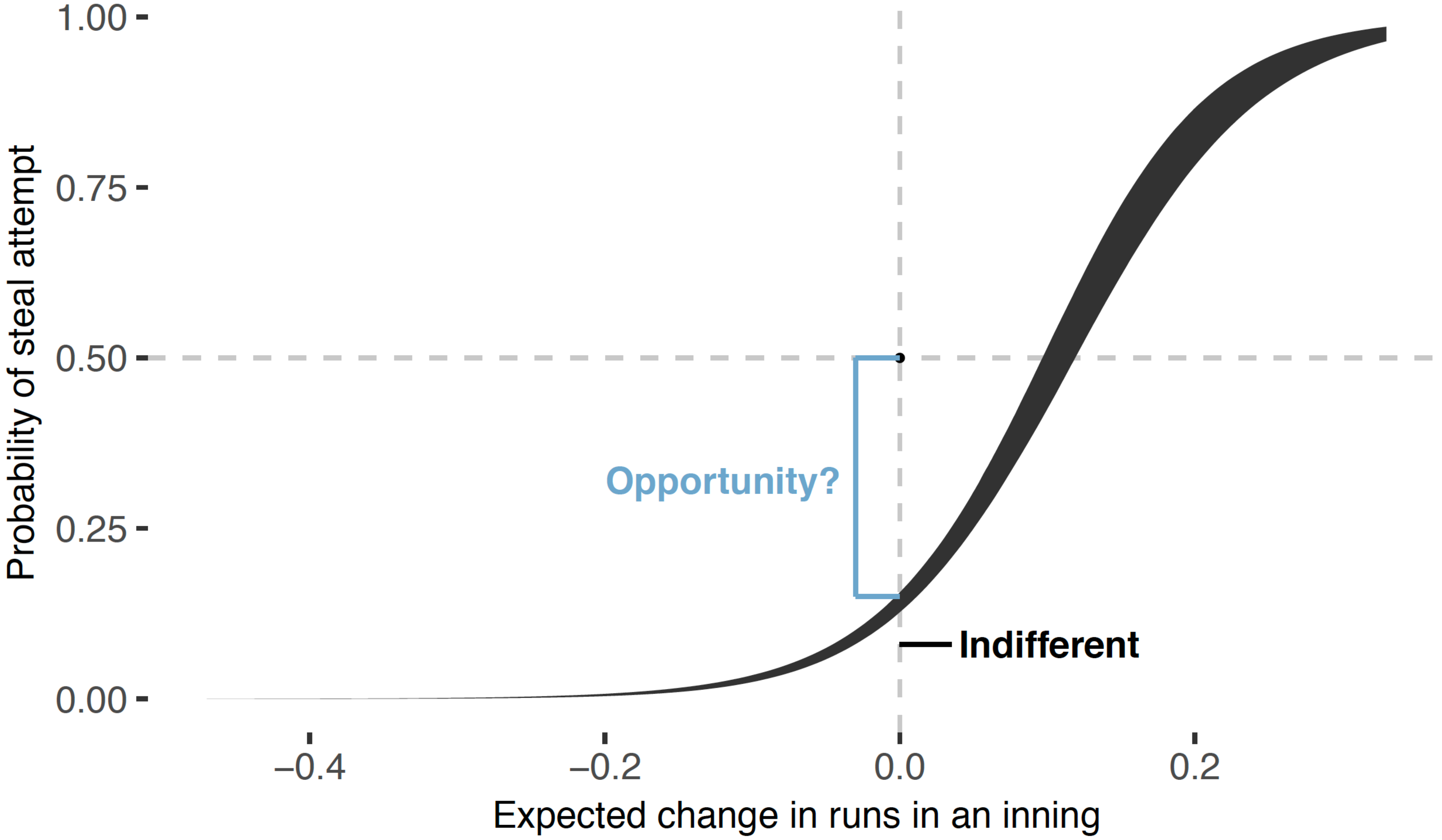


Dodgers *draft* proposal example



Dodgers *draft* proposal example



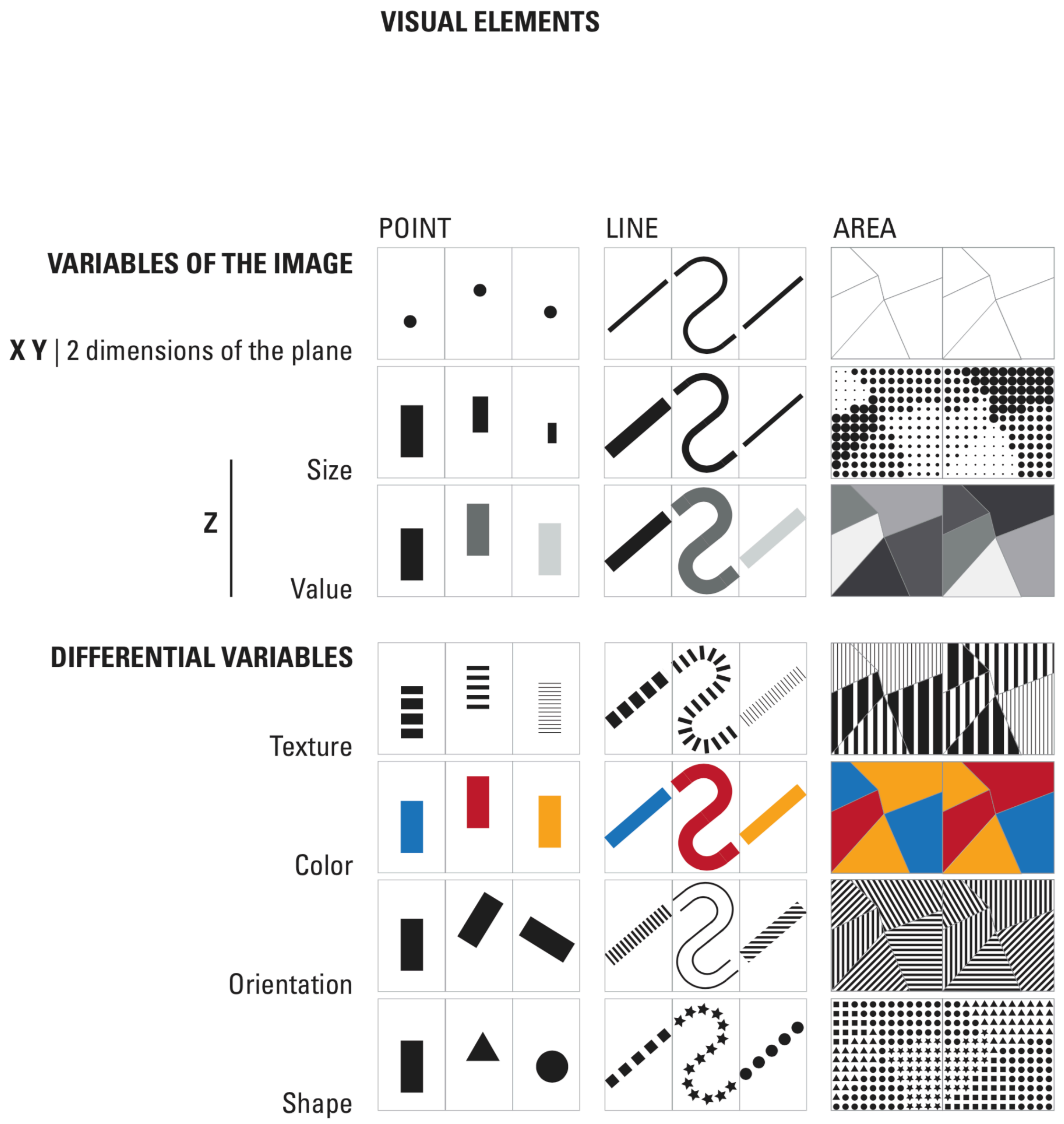


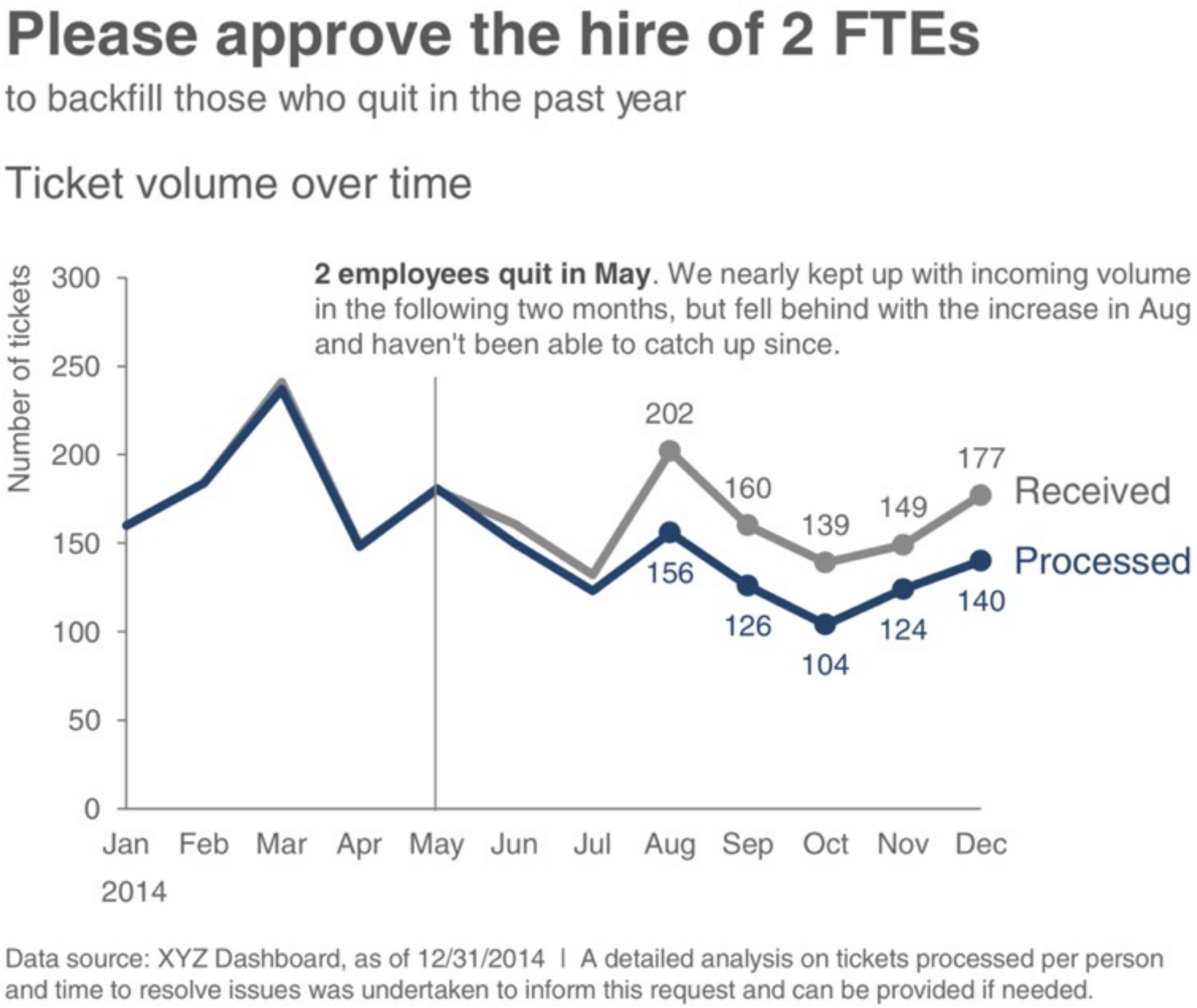
adding dimensions through small multiples

Citi Bike example — *exploratory data analysis*

class exercises

exercise, identify data encodings in visual channels





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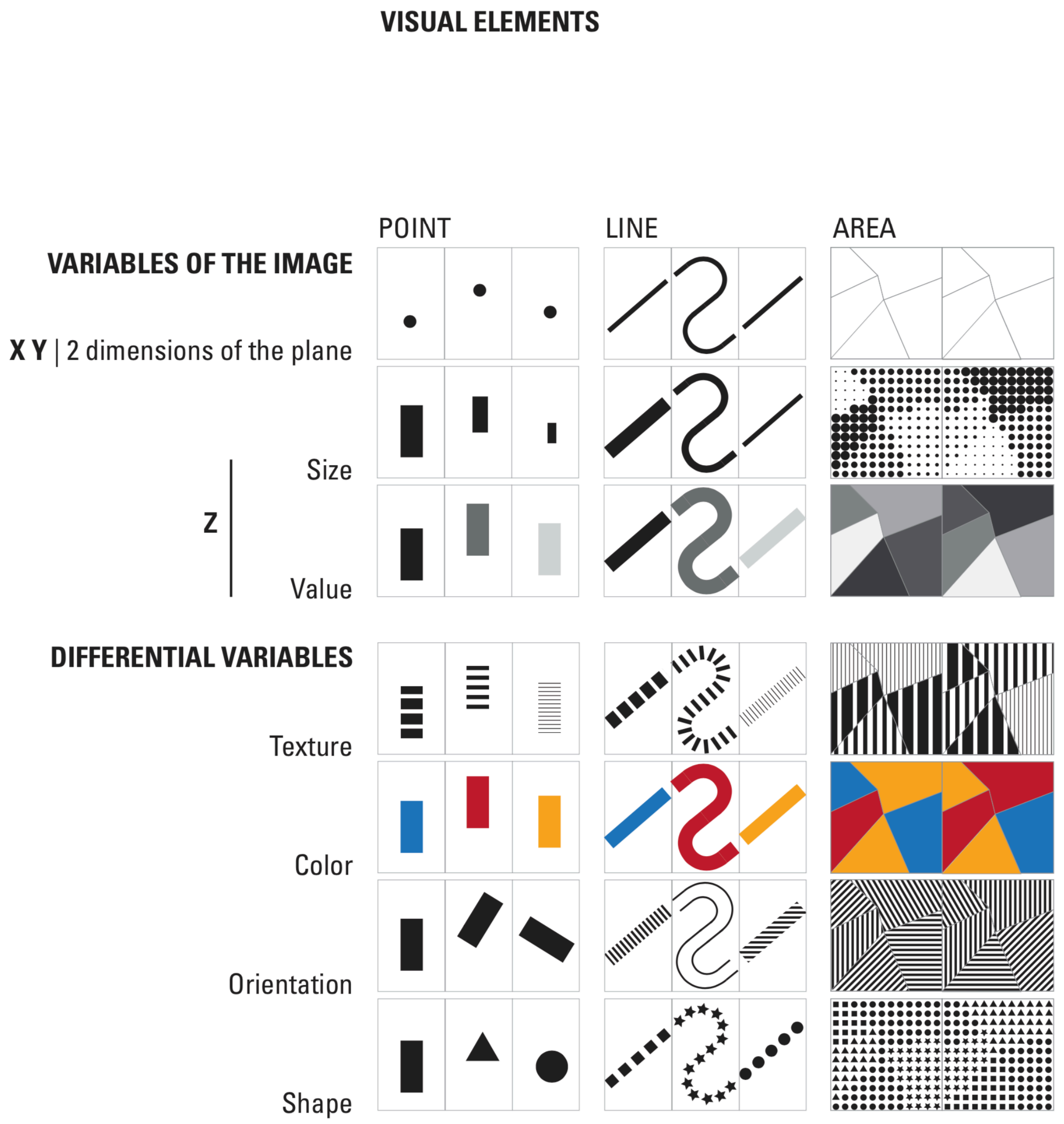
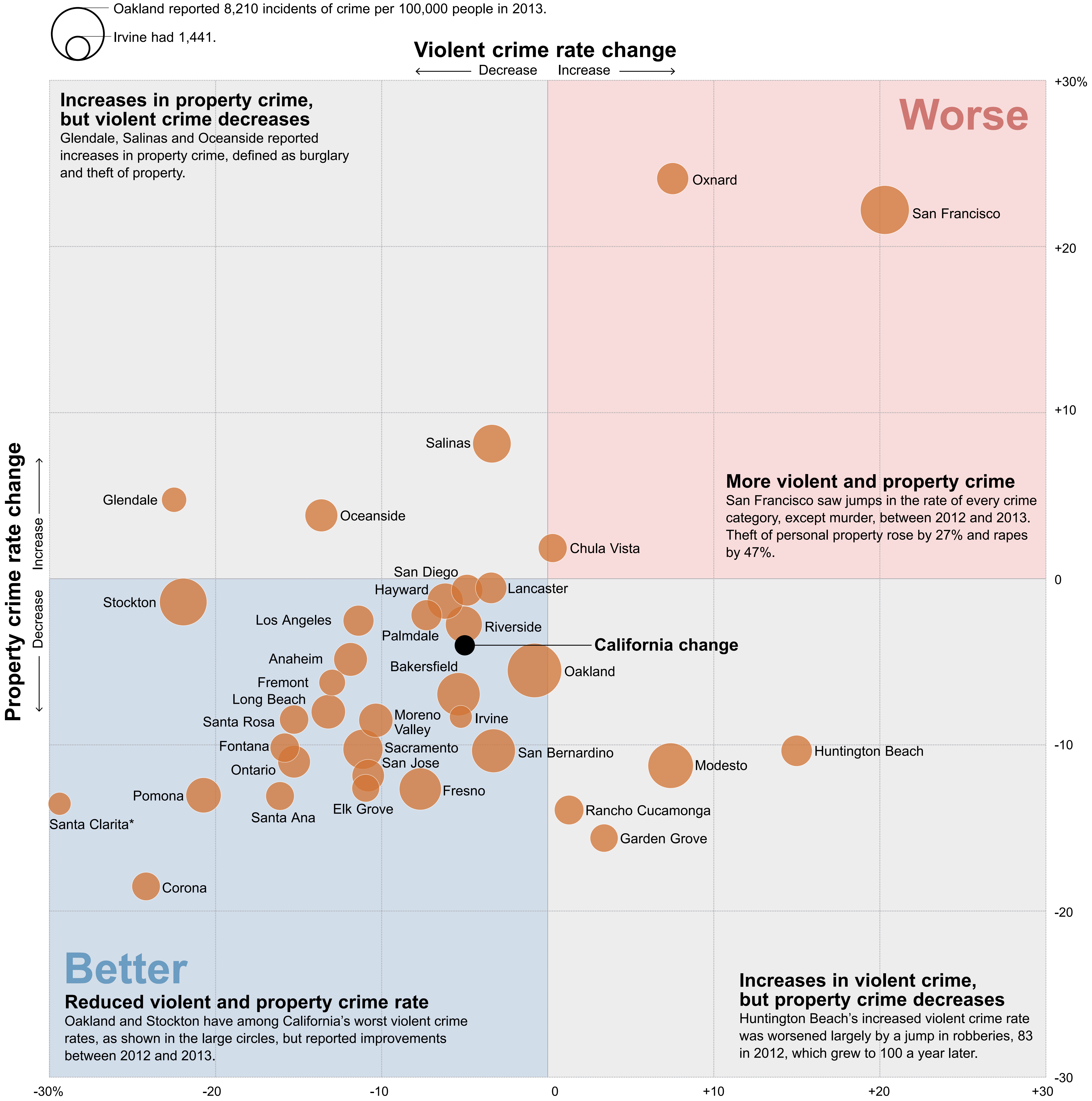
exercise, identify data encodings in visual channels





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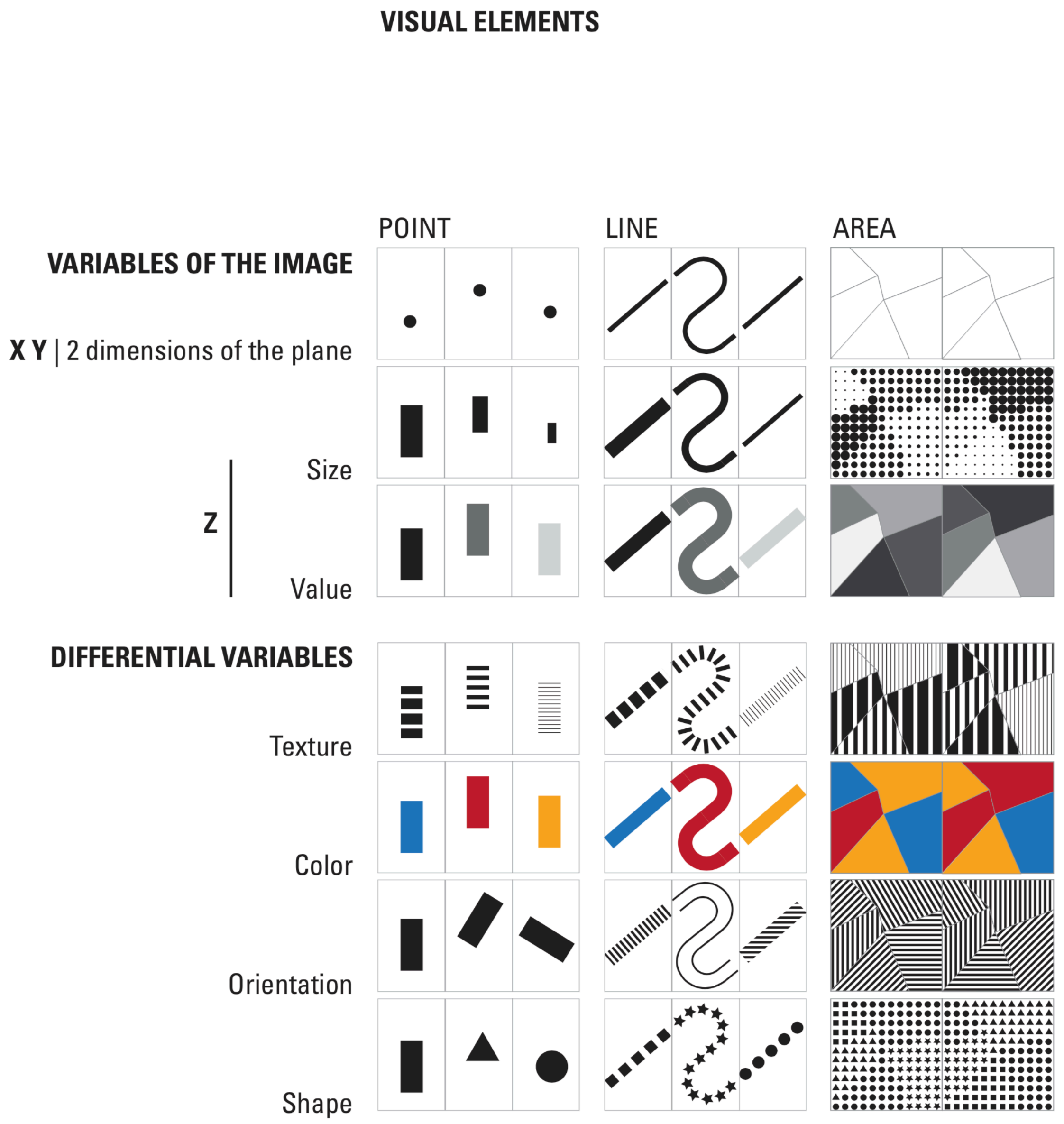
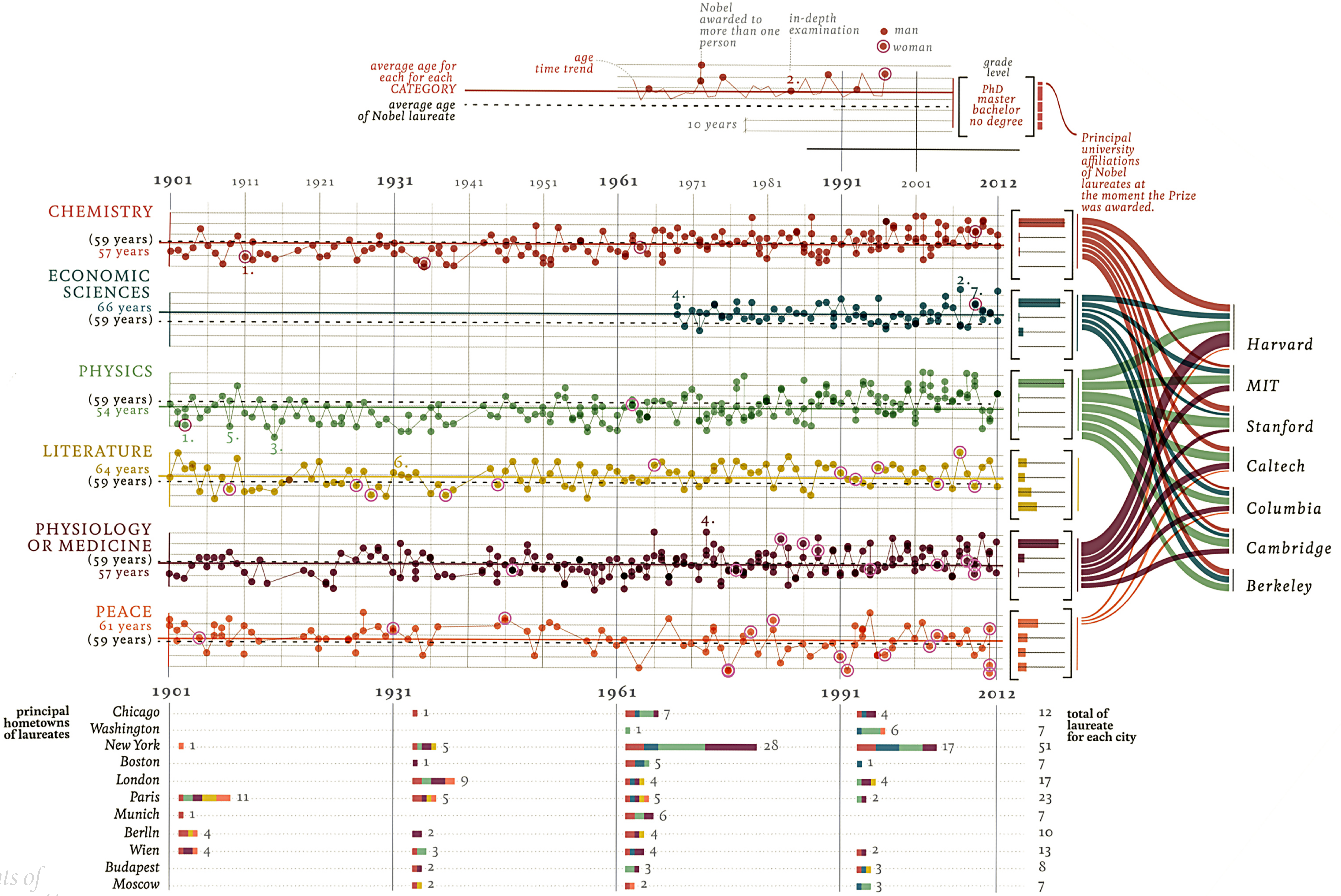
exercise, identify data encodings in visual channels





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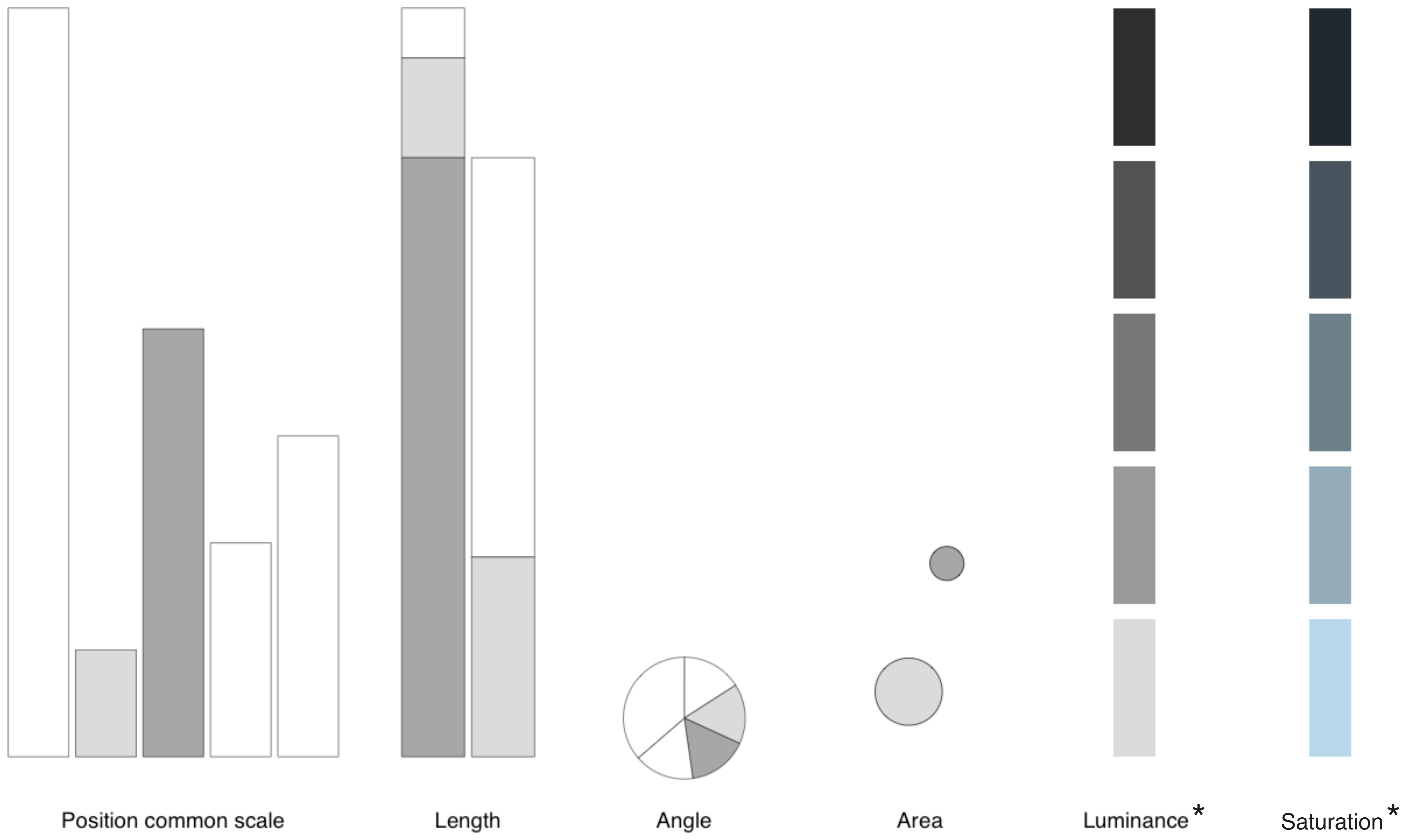
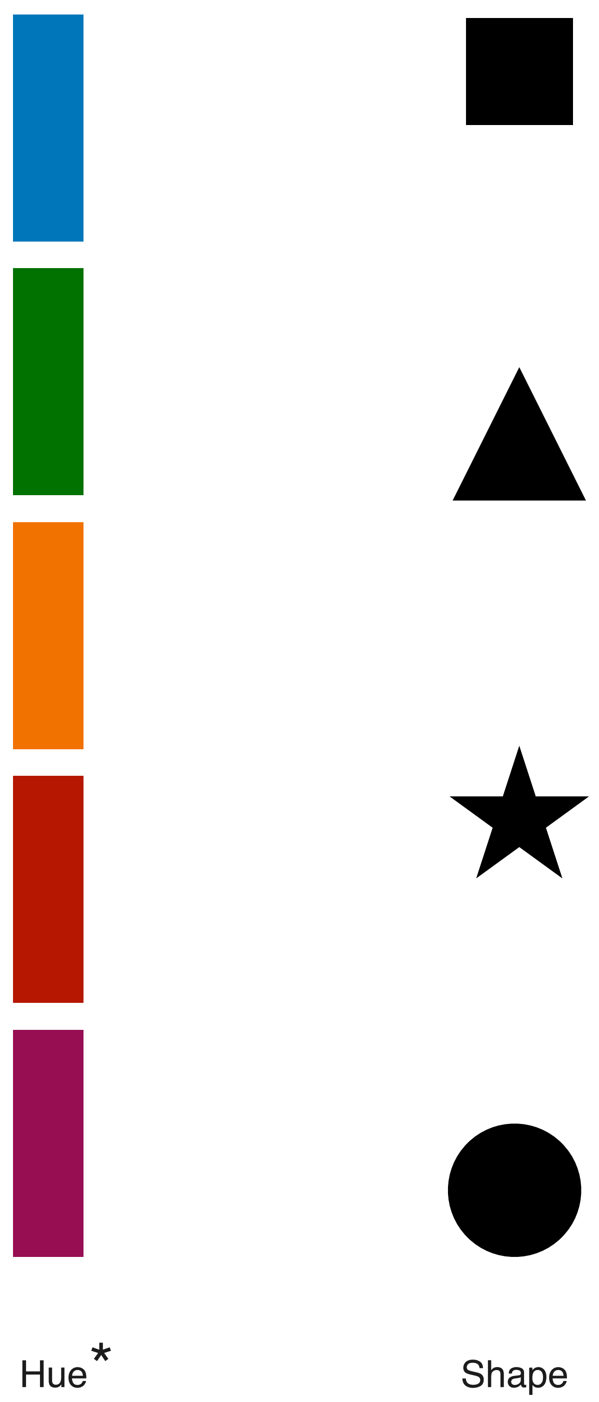
channel effectiveness for encoding data

ratio, interval, and ordered



more effective ⟷ **less effective**

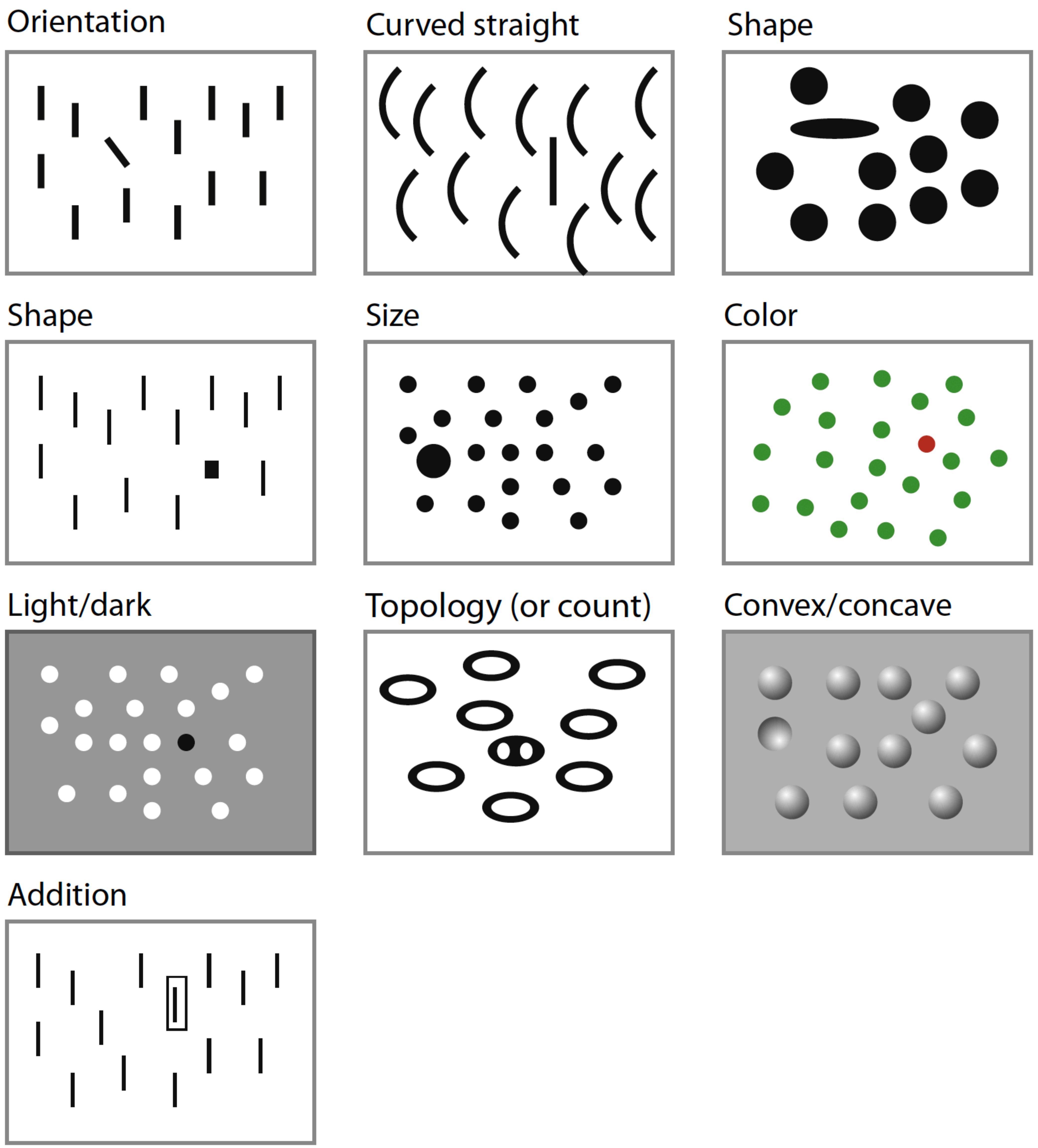
categorical



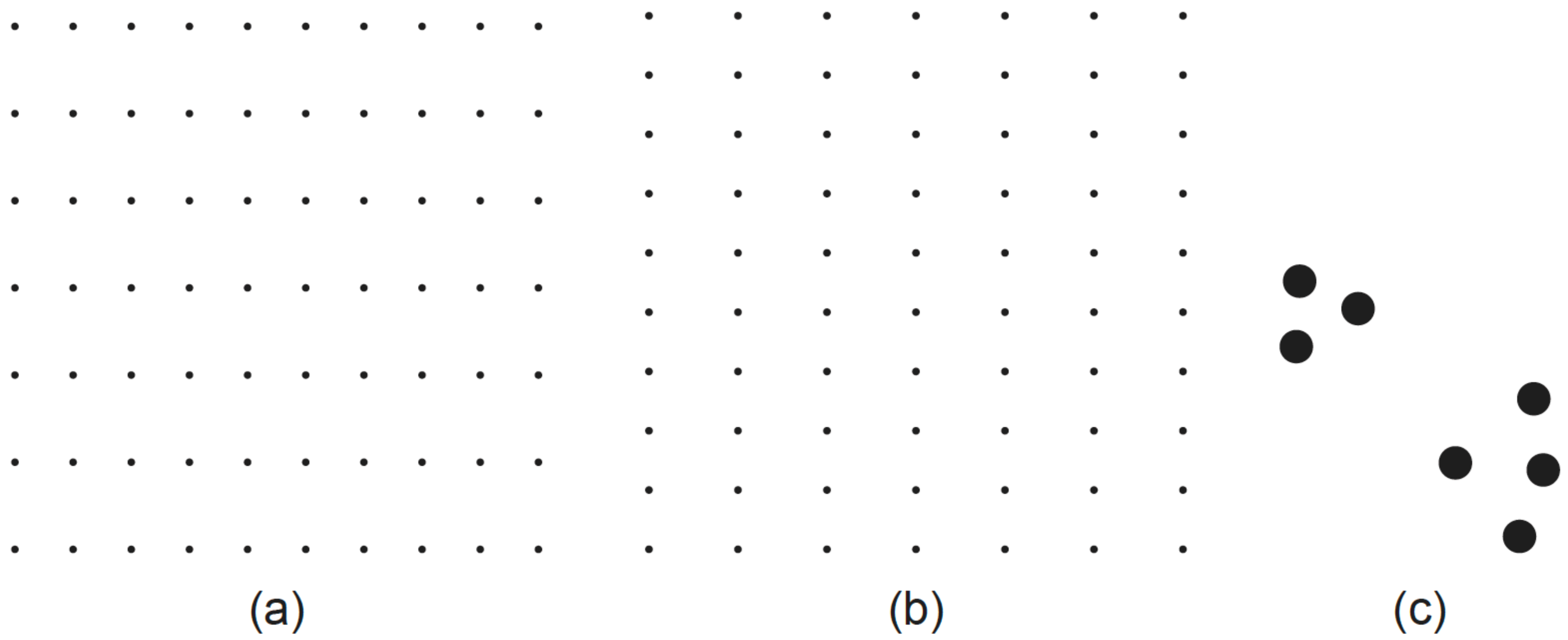
more effective ⟷ **less effective**

perceptual psychology

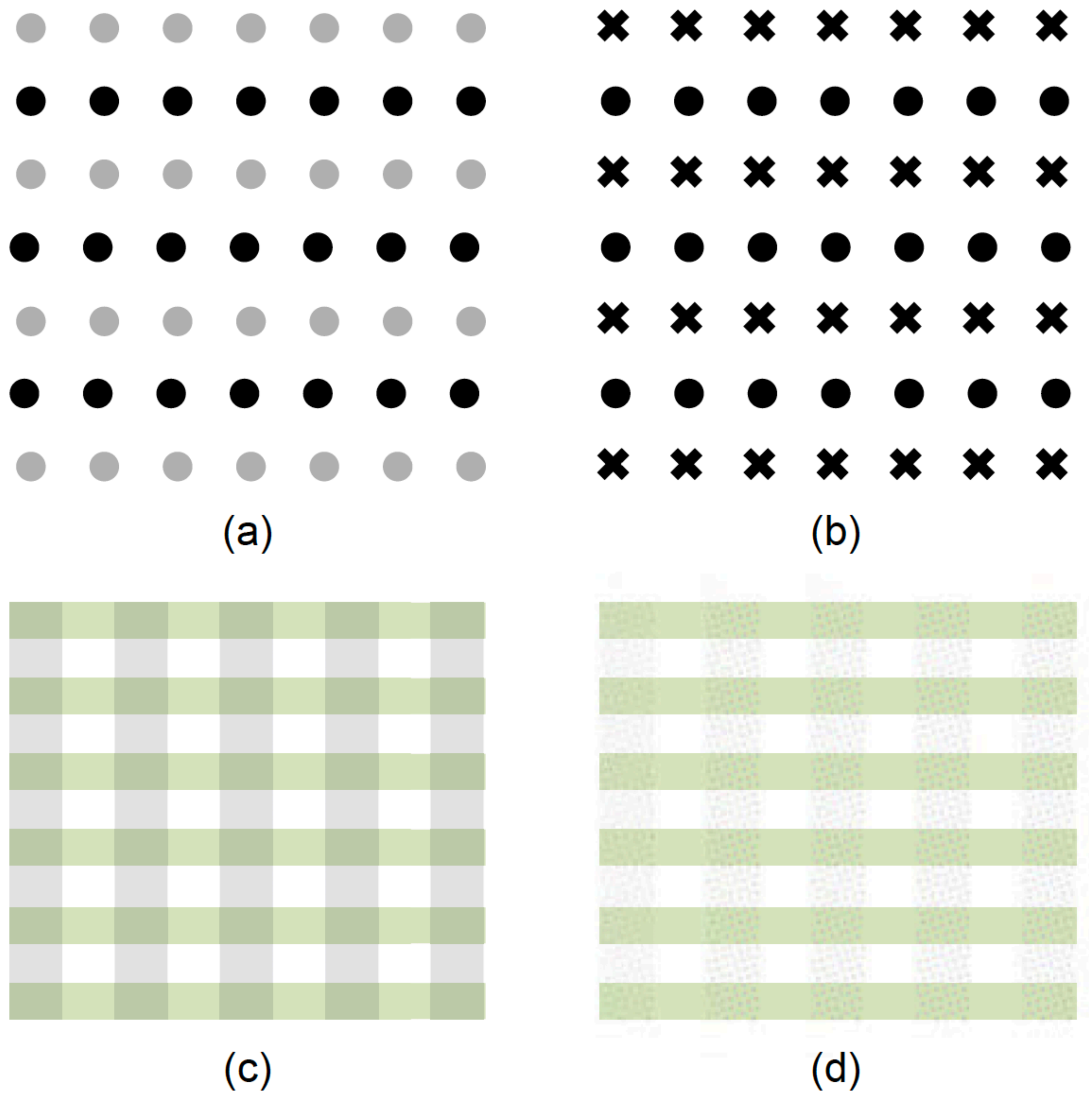
perceptual psychology, *pre-attentive attributes*

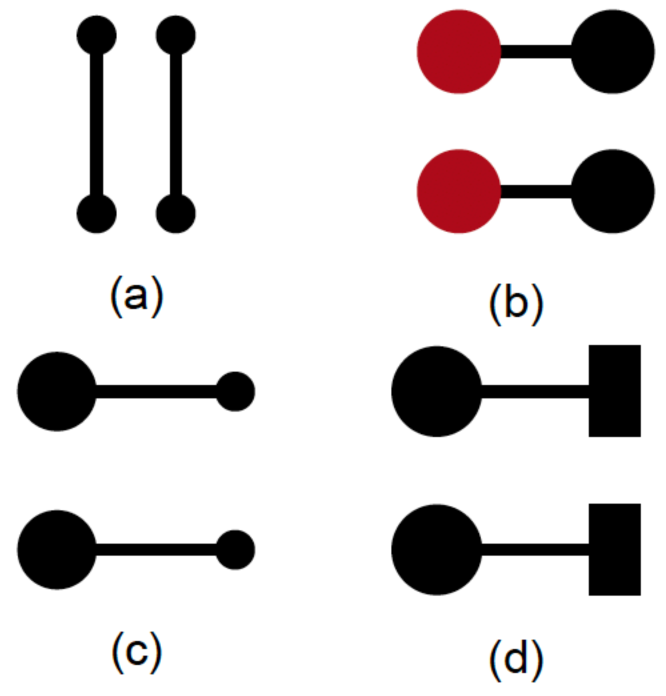


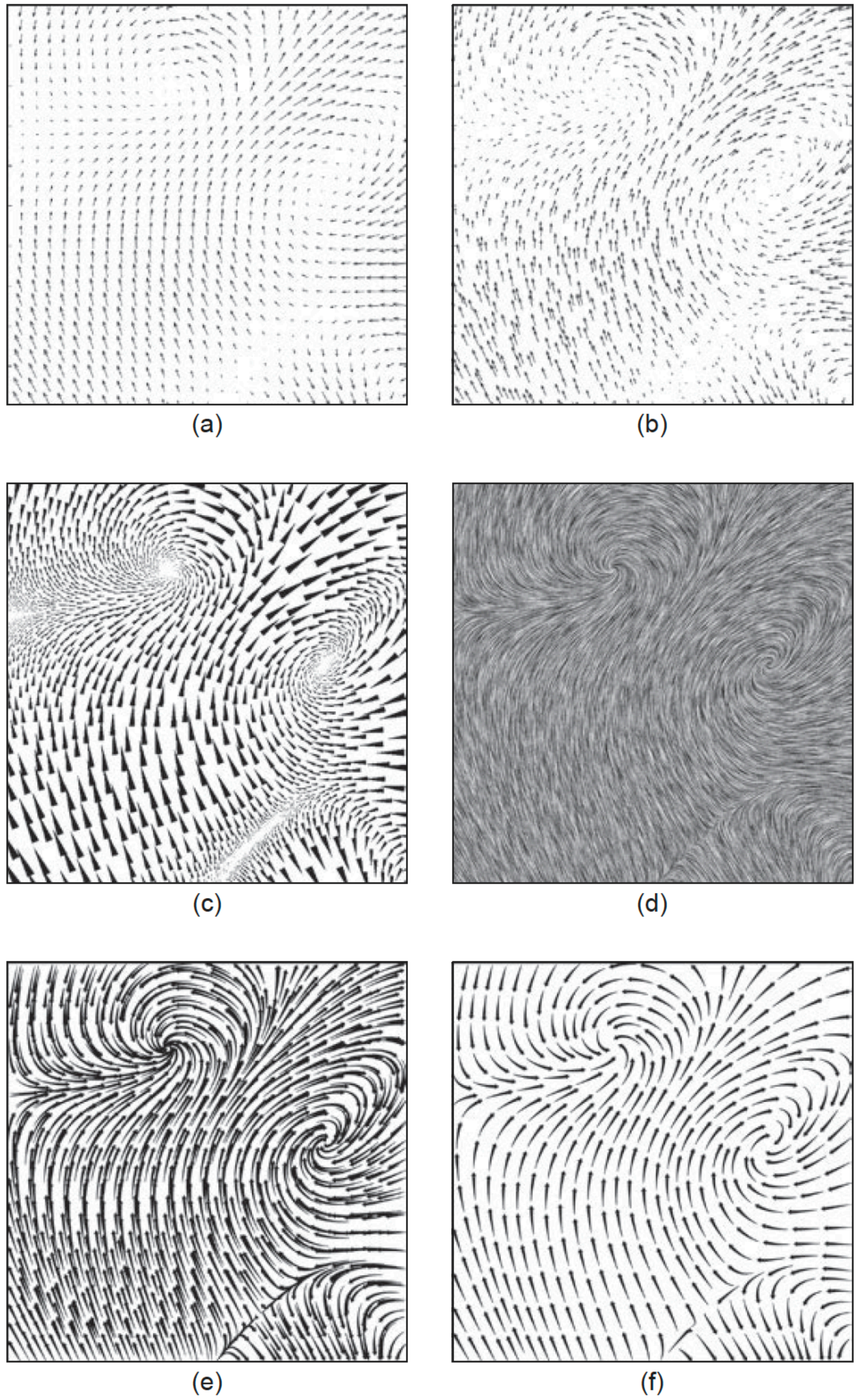
perceptual psychology, Gestalt principles, *proximity*

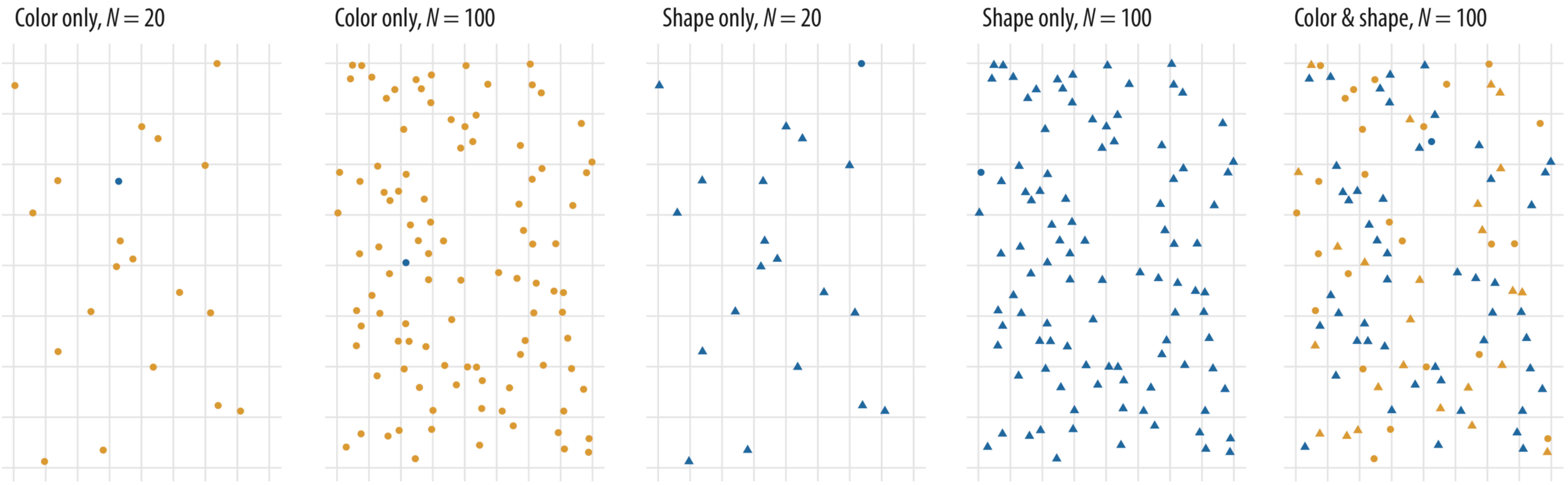


 Gestalt principles, *similarity*

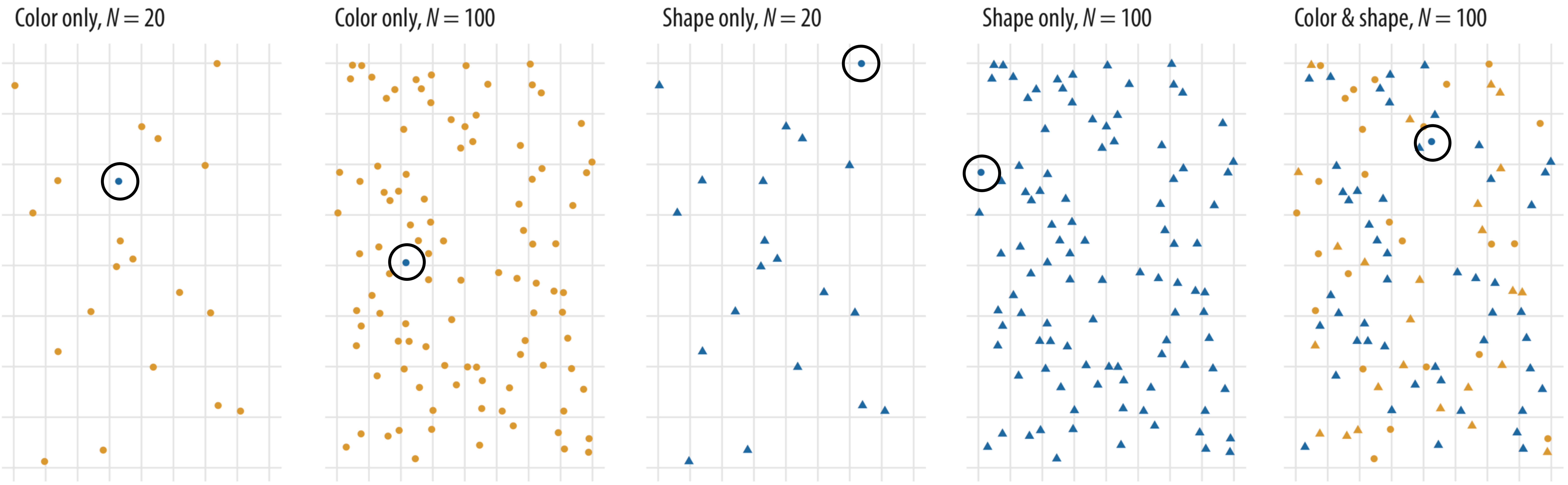



(a)
(b)
(c)
(d)


(a)
(b)
(c)
(d)
(e)
(f)


Color only, $N = 20$
Color only, $N = 100$
Shape only, $N = 20$
Shape only, $N = 100$
Color & shape, $N = 100$

perceptual psychology, example — *focusing visual attention*



resources

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