Correlation

Measures the linear relationship between objects

$$corr(\mathbf{x}, \mathbf{y}) = \frac{covariance(\mathbf{x}, \mathbf{y})}{standard_deviation(\mathbf{x}) * standard_deviation(\mathbf{y})} = \frac{s_{xy}}{s_x s_y}, (2.11)$$

where we are using the following standard statistical notation and definitions

covariance(
$$\mathbf{x}, \mathbf{y}$$
) = $s_{xy} = \frac{1}{n-1} \sum_{k=1}^{n} (x_k - \overline{x})(y_k - \overline{y})$ (2.12)

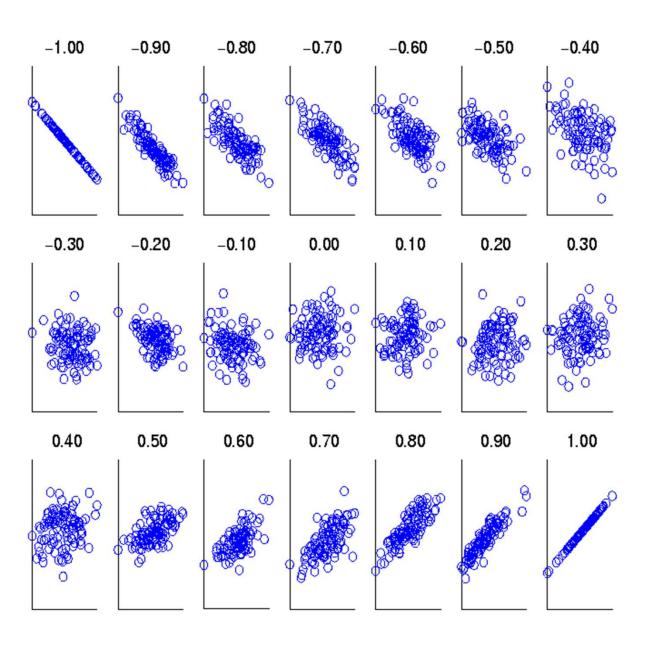
standard_deviation(
$$\mathbf{x}$$
) = $s_x = \sqrt{\frac{1}{n-1} \sum_{k=1}^{n} (x_k - \overline{x})^2}$

standard_deviation(
$$\mathbf{y}$$
) = $s_y = \sqrt{\frac{1}{n-1} \sum_{k=1}^{n} (y_k - \overline{y})^2}$

$$\overline{x} = \frac{1}{n} \sum_{k=1}^{n} x_k$$
 is the mean of \mathbf{x}

$$\overline{y} = \frac{1}{n} \sum_{k=1}^{n} y_k$$
 is the mean of \mathbf{y}

Visually Evaluating Correlation

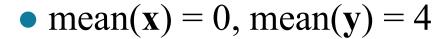


Scatter plots showing the similarity from -1 to 1.

Drawback of Correlation

- $\mathbf{x} = (-3, -2, -1, 0, 1, 2, 3)$
- $\mathbf{y} = (9, 4, 1, 0, 1, 4, 9)$

$$y_i = x_i^2$$



• std(x) = 2.16, std(y) = 3.74

9 8 7 6 >-5 4 3 2 1 0 -4 -2 0 2 4

•
$$corr = (-3)(5)+(-2)(0)+(-1)(-3)+(0)(-4)+(1)(-3)+(2)(0)+3(5) / (6 * 2.16 * 3.74)$$

= 0

Correlation vs Cosine vs Euclidean Distance

- Compare the three proximity measures according to their behavior under variable transformation
 - scaling: multiplication by a value
 - translation: adding a constant

Property	Cosine	Correlation	Euclidean Distance
Invariant to scaling (multiplication)	Yes	Yes	No
Invariant to translation (addition)	No	Yes	No

- Consider the example
 - $\mathbf{x} = (1, 2, 4, 3, 0, 0, 0), \mathbf{y} = (1, 2, 3, 4, 0, 0, 0)$
 - $y_s = y * 2$ (scaled version of y), $y_t = y + 5$ (translated version)

Measure	(x , y)	(x , y _s)	(x, y_t)
Cosine	0.9667	0.9667	0.7940
Correlation	0.9429	0.9429	0.9429
Euclidean Distance	1.4142	5.8310	14.2127