Extract from:
Bradley Efron and Trevor Hastie
Computer Age Statistical Inference: Algorithms, Evidence, and Data Science
Cambridge University Press, 2016
https://web.stanford.edu/~hastie/CASI_files/PDF/casi.pdf

Modern Bayesian practice uses various strategies to construct an appropriate "prior" g(μ)in the absence of prior experience, leaving many statisticians unconvinced by the resulting Bayesian inferences. Our second example illustrates the difficulty.

Table 3.1 *Scores from two tests taken by 22 students*, mechanics *and* vectors.

```
mechanics1 <- c(7,44,49,59,34,46,0,32,49,52,44)
mechanics2 <- c(36,42,5,22,18,41,48,31,42,46,63)
vectors1 <- c(51,69,41,70,42,40,40,45,57,64,61)
vectors2 <- c(59,60,30,58,51,63,38,2,69,49,63)
table1 <- data.frame("mechanics"=mechanics1,"vectors"=vectors1)
rownames(table1) <- 1:11

table2 <- data.frame("mechanics"=mechanics2,"vectors"=vectors2)
rownames(table2) <- 12:22

kable(t(table1))
```

	1	2	3	4	5	6	7	8	9	10	11
mechanics	7	44	49	59	34	46	0	32	49	52	44
vectors	51	69	41	70	42	40	40	45	57	64	61

```
kable(t(table2))
```

	12	13	14	15	16	17	18	19	20	21	22
mechanics	36	42	5	22	18	41	48	31	42	46	63
vectors	59	60	30	58	51	63	38	2	69	49	63

Table 3.1 shows the scores on two tests, mechanics and vectors, achieved by n = 22 students. The sample correlation coefficient between the two scores is $\hat{\theta}$ =0.498,

$$\hat{\theta} = \sum_{i=1}^{22}(m_i - \bar{m})(v_i - \bar{v})/[\sum_{i=1}^{22}(m_i - \bar{m})^2 \sum_{i=1}^{22}(v_i - \bar{v})^2]^{\frac{1}{2}}$$

with m and v short for mechanics and vectors, $\bar{m}$ and $\bar{v}$ their aver- ages.