***CL*: The Common Language Effect Size Statistic**[©]

McGraw and Wong (1992, *Psychological Bulletin*, *111*: 361-365) proposed an effect size statistic which for a two group design with a continuous dependent variable is **the probability that a randomly selected score from the one population will be greater than a randomly sampled score from the other population**. As an example they use sexual dimorphism in height among young adult humans. National statistics are mean = 69.7 inches (*SD* = 2.8) for men, mean = 64.3 inches (*SD* = 2.6) for women. If we assume that the distributions are normal, then the probability that a randomly selected man will be taller than a randomly selected woman is 92%, thus the ***CL*** is 92%. They argue that the ***CL*** is a statistic more likely to be understood by statistically naive individuals than are the other available effect size statistics. I'll reserve judgment on that (naive persons have some funny ideas about probabilities), but it may help you get a better feel for effect sizes. I assume they use sex differences because most of us already have a pretty good feeling for how much the sexes differ on things like height and weight.

To calculate the ***CL*** with independent samples McGraw and Wong instruct us to compute $Z = \frac{|M_1 - M_2|}{\sqrt{S_1^2 + S_2^2}}$ and then find the probability of obtaining a Z less than the computed value. For the height example, $Z = \frac{69.7 - 64.3}{\sqrt{2.8^2 + 2.6^2}} = 1.41$ and P(Z < 1.41) = 92%. Alternatively, one can compute the ***CL*** from the more common effect size statistic **d**. If we have weighted the two samples variances equally when computing **d**, that is, $\hat{d} = \frac{M_1 - M_2}{\sqrt{\frac{S_1^2 + S_2^2}{2}}}$, then we can compute the Z for the ***CL*** as **d** divided by √2. For the height data, $\hat{d} = \frac{69.7 - 64.3}{\sqrt{\frac{2.8^2 + 2.6^2}{2}}} = 2.00$ and $Z = \frac{2}{\sqrt{2}} = 1.41$. In their article McGraw and Wong computed **d** with a weighted (by sample sizes) mean variance, that is, $\hat{d} = \frac{M_1 - M_2}{\sqrt{p_1 S_1^2 + p_2 S_2^2}}$, where $p_i = \frac{n_i}{N}$. They used this weighted mean variance even though they were comparing men with women, where in the population there are about equal numbers in both groups (for some of their variables they had much more data from men than from women). I would have weighted the two variances equally.

McGraw and Wong gave hypothetical examples of group differences in IQ (*SD* = 15) and computed **d**, ***CL***, and four other effect size statistics (including the binomial effect size display). I reproduce the table without the other four effect size statistics but with my addition of examples corresponding to Cohen's small (**d** = .2), medium (**d** = .5) and large (**d** = .8) effect sizes.

Mean 1	Mean 2	d	*CL*	Odds		Mean 1	Mean 2	d	*CL*	*Odds*
100	100	0.00	50%	1		90	110	1.33	83%	4.88
98.5	101.5	0.20	56%	1.27		85	115	2.00	92%	11.5
96.25	103.75	0.50	64%	1.78		80	120	2.67	97%	32.3
95	105	0.67	68%	2.12		75	125	3.33	99%	99
94	106	0.80	72%	2.57						

McGraw and Wong also provide **d** and ***CL*** (and the other four effect size statistics) from some actual large sample studies of sex differences. I list some of those statistics here just to give you a feel for **d** and ***CL***.

Variable	Male Mean	Female Mean	**d**	***CL***	***Odds***
Verbal ACT	17.9	18.9	0.19	55%	1.22
Math ACT	18.6	16.1	0.48	63%	1.70
Aggressiveness	9.3	6.9	0.62	67%	2.03
Mental Rotation	23	15	0.91	74%	2.85
Weight	163	134	1.07	78%	3.55
Leg Strength	212	94	1.66	91%	10.11

McGraw and Wong opined that with correlated samples one should use the variance sum law to get the denominator of the *Z*, that is, $Z = \frac{|M_1 - M_2|}{\sqrt{S_1^2 + S_2^2 - 2rS_1S_2}}$. I think this inappropriate, as it will lead to overestimation of the effect size. IMHO, one should compute the ***CL*** in the same way, regardless of whether the design was independent samples or correlated samples. McGraw and Wong also show how to extend the ***CL*** statistic to designs with more than two groups and designs with a categorical dependent variable, but I don't think the ***CL*** statistic very useful there.

Dunlap (1994, *Psychological Bulletin*, *116*: 509-511) has extended the ***CL*** statistic to bivariate normal correlations. Assume that we have randomly sampled two individuals' scores on X and Y. If individual 1 is defined as the individual with the larger score on X, than the ***CL*** statistic is the probability that individual 1 also has the larger score on Y. Alternatively the ***CL*** statistic here can be interpreted as the probability that an individual will be above the mean on Y given that we know e is above the mean on X. Given *r*, $CL = \frac{\sin^{-1}(r)}{\pi} + .5$. Dunlap uses Karl Pearson's (1896) data on the correlation between fathers' and sons' heights (*r* = .40). ***CL*** = 63%. That is, if Joe is taller than Sam, then there is a 63% probability that Joe's son is taller than Sam's son. Put another way, if Joe is taller than average, then there is a 63% probability that Joe's son is taller than average too. Here is a little table of ***CL*** statistics for selected values of *r*, just to give you a feel for it.

r	.00	.10	.20	.30	.40	.50	.60	.70	.80	.90	.95	.99
CL	50%	53%	56%	60%	63%	67%	70%	75%	80%	86%	90%	96%

One interesting use of the CL is as a nonparametric effect size statistic for comparing the locations of two groups of scores.

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