Research Note: Dual Calibration

Charles Ragin (cragin@uci.edu)

August 29, 2023

Background

The first step in any set-analytic investigation, using either crisp or fuzzy sets, is the specification and construction of the relevant sets, including both the causal conditions and the outcome. Three main phases in this process are: (1) the identification of relevant conditions and outcomes, (2) the conceptualization of these conditions and outcomes as sets, and (3) the assignment of membership scores. With crisp sets, membership scores are either "1" (in the set) or "0" (out of the set). With fuzzy sets, scores range from 0 to 1, indicating the degree of membership of each case in a given set. When interval-scale variables are used as the basis for constructing fuzzy sets, the third phase involves specifying empirical benchmarks to structure the translation of variable scores to fuzzy membership scores (see Ragin 2008, chapter 5).

The translation of variables to sets involves an important reconceptualization of the underlying constructs. For example, "income" is easy to understand as a variable. However, in its "raw" form, it makes no sense as a set. The key difference between variables and fuzzy sets parallels the distinction between abstract nouns and adjectives. For example, "income" is an abstract noun, and abstract nouns make good variable names. Adding an adjective to create "high income," by contrast, distinguishes a specific category or range of values and thus is a good starting point for constructing a fuzzy set. Another example: "education," an abstract noun, describes a variable; "college-educated," an adjective, describes a set.

The "variable/abstract noun" versus "set/adjective" distinction offers a good basis for understanding the second phase of calibration—the conceptualization of conditions and outcomes as sets. The set labels selected by the investigator should describe some case aspect that can be used as a basis for distinguishing cases in a qualitative manner (e.g., "*high* income"). With crisp sets, the assignment of cases to sets is all or nothing—in or out. Fuzzy sets, by contrast, allow partial membership in qualitative states and are thus simultaneously qualitative and quantitative (Ragin 2000: 153-155).

To calibrate interval-scale variables as fuzzy sets, most QCA researchers use the "direct method" of calibration discussed in chapter 5 of Ragin (2008). This method is based on the specification of selected interval variable values as indicating: (1) the threshold for full membership in the target set, which is translated to a fuzzy-set membership score of 0.95; (2) the threshold for full non-membership in the target set, which is translated to a fuzzy-set membership score of 0.05; and (3) the cross-over point, which is the dividing line between being "more in" versus "more out" of the target set, which is a fuzzy-set membership score of 0.50. The end result is typically an S-shaped curve, with low scores on the interval-scale variable approaching a score of 0 on the fuzzy set and high scores on the interval-scale variable approaching 1.0. The calibration procedure is automated in the software package fuzzy-set Qualitative Comparative Analysis (fsQCA) and is based on the user's specification of the three benchmark values just described.

Both crisp and fuzzy sets can be negated simply by subtracting set membership scores from 1. For example, suppose democratic countries are coded 1 and not-democratic countries are coded 0. Subtracting these two values from 1 reverses their scores. Likewise for fuzzy sets, a case with a membership score of 0.8 in "high income" has a membership score of 1 – 0.8 = 0.2 in "not-high income." It is important to be consistent in the labelling of the negated set; it should be labelled in a way that makes it clear that it is the negation of another set. For example, the negation of degree of membership in "high income" is *not* degree of membership in "low income." Degree of membership in "low income" should be conceptualized separately from the conceptualization of "high income." Too often, QCA researchers fail to recognize the importance of consistent conceptualization and labelling of negated sets. While it might seem appropriate for the negation of "high income" to be labelled "low income," there is an important difference between "not-high" and "low." A middle-income person with low membership in "high income" can also have low membership in "low income."

This research note introduces the method of *dual calibration*, along with a demonstration of the use of fsQCA software to implement the procedure. The method allows simultaneous calibration of "high-X versus not-high-X" and "low-X versus not-low-X" using four benchmark values instead of three. Using three, which is the usual practice, yields a single fuzzy set ranging from high-X to not-high-X. Using four benchmarks yields two fuzzy sets, one ranging from high-X to not-high-X and the other ranging from low-X to not-low-X.

Dual Calibration

It is often necessary to create more than one fuzzy set from a single source variable. Consider, for example, the causal conditions linked to poverty versus the causal conditions linked to having a well-paying job. Years of education has an impact on both outcomes. When thinking in terms of variables, and not sets, it would be routine to examine the correlation between years of education and these two outcomes. Education has a negative correlation with poverty and a positive correlation with having a well-paying job. When thinking in terms of sets, however, it is necessary to abandon abstract nouns like "education" and think in terms of sets and the adjectives that describe them. It is the "set of low-education respondents" who tend to end up in poverty and the set of "high-education respondents" who tend to end up with well-paying jobs. To examine these connections with set-analytic methods, it is necessary to calibrate education in two different ways, focusing on different ends of the distribution.

Consider the translation of years of education to the fuzzy set of respondents with low education and its negation, the set of respondents with not-low education:

	Membership in low education	**Membership in not-low education**
4 years	0.99	0.01
6 years	0.95	0.05
10 years	0.75	0.25
12 years	0.50	0.50
14 years	0.25	0.75
16 years	0.05	0.95
18 years	0.02	0.98
20 years	0.01	0.99

Using fsQCA's calibration procedure, to translate years of education into the fuzzy set of respondents with low education, the following command is executed:
compute lowed = calibrate(education,6,12,16)
where *education* is a variable in the dataset, measured in years, and *lowed* is the newly created fuzzy set. The first listed number (6) is the benchmark value for a fuzzy membership of 0.95; the second listed number (12) corresponds to the cross-over fuzzy score (0.5); the third listed number (16) corresponds to a fuzzy membership score of 0.05. The calculation of membership in the set of respondents with not-low education is simply:
compute notlowed = 1 – lowed

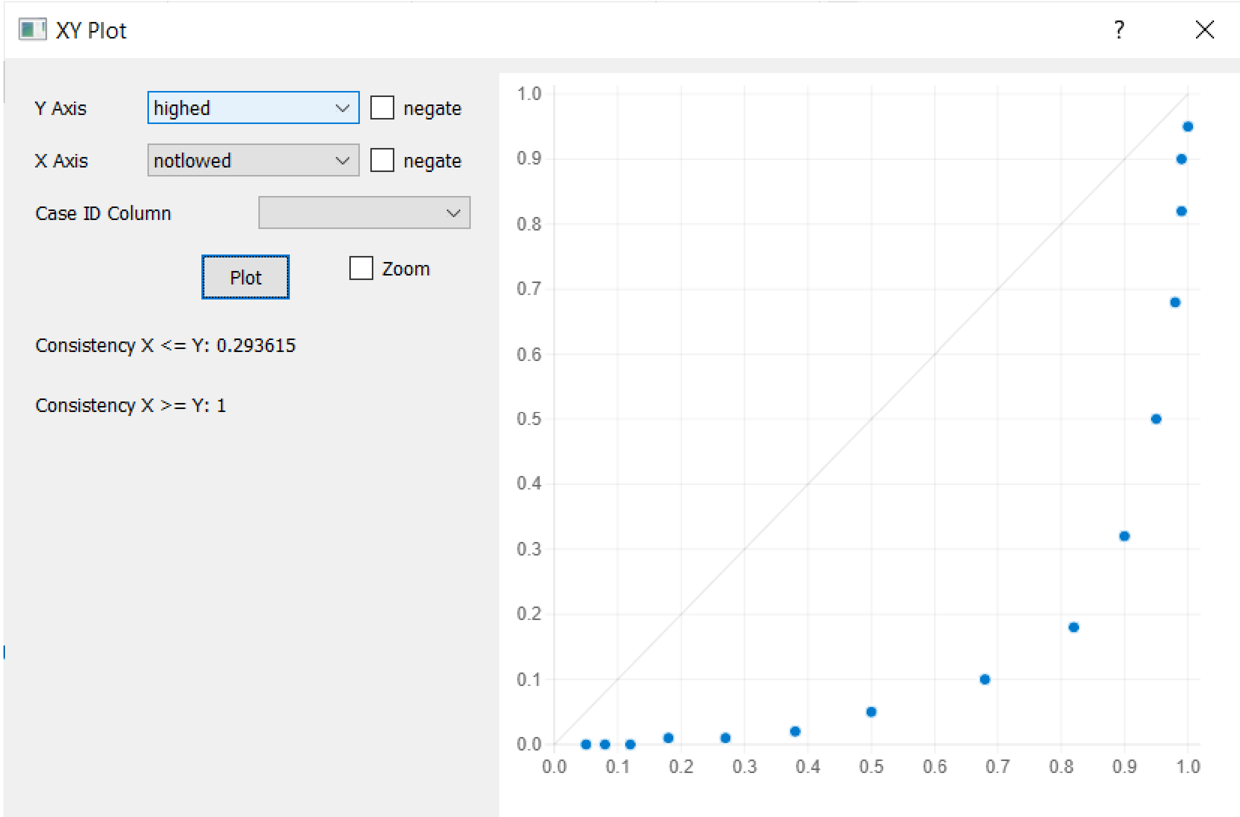
Next, consider the translation of years of education into the fuzzy set of respondents with high education and its negation, the set of respondents with not-high education:

	Membership in high education	**Membership in not-high education**
4 years	0.01	0.99
6 years	0.01	0.99
10 years	0.02	0.98
12 years	0.05	0.95
14 years	0.25	0.75
16 years	0.50	0.50
18 years	0.75	0.25
20 years	0.95	0.05

To translate years of education to the fuzzy set of respondents with high education, the following command is executed in fsQCA:
compute highed = calibrate(education,20,16,12)
where education is a variable in the dataset and *highed* is the newly created fuzzy set. The first listed number (20) is the benchmark value for a fuzzy membership score of 0.95; the second listed number (16) corresponds to the cross-over fuzzy score (0.5); the third listed number (12) corresponds to a fuzzy membership score of 0.05. The calculation of membership in the set of respondents with not-high education is simply:
compute nothighed = 1 – highed

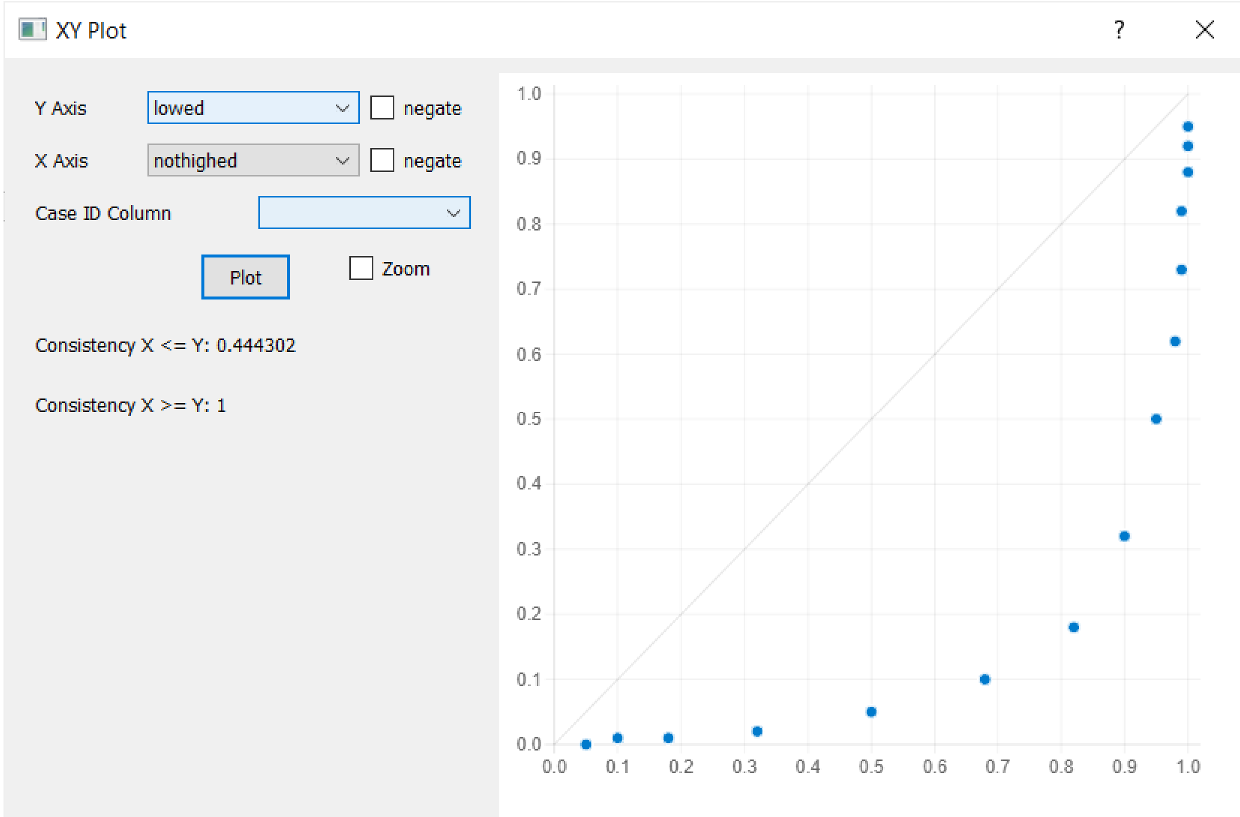
The difference between the two calibrations can be clearly seen in the plot of *highed* against *notlowed* and in the plot of *lowed* against *nothighed*. First, consider *highed* against *notlowed*, shown in Figure 1. The difference is striking. Moderately high membership scores in *notlowed* (e.g., in the 0.7 to 0.9 range) are linked to low membership scores in *highed* (e.g., scores in the 0.1 to 0.3 range). The two calibrations converge only when both membership scores are very close to 0 or to 1.

Figure 1: Plot of *highed* against *notlowed.*



Next, consider the plot of *lowed* against *nothighed*, shown in Figure 2. The pattern is virtually identical to the first plot. Again, scores in the 0.7 to 0.9 range of *nothighed* are paired with scores in the 0.1 to 0.3 range of *lowed,* and the two calibrations converge only when both membership scores are very close to 1 or to 0. Notice also that in both plots the superset consistency calculation ($X_i \geq Y_i$) is equal to 1, indicating that the Y axis values are uniformly less than or equal to the X axis values. Thus, *highed* is a subset of *notlowed*, and *lowed* is a subset of *nothighed*, which is consistent with common sense. For example, it is easier to achieve not-low education than it is to achieve high education.

Figure 2: Plot of *lowed* against *nothighed*.



Dual Calibration Using fsQCA

While it is perfectly acceptable to calibrate high and low using separate commands, as in the example just provided, dual calibration is automated in fsQCA. A single command generates two calibrated sets, one with the suffix HI and another with the suffix LO. For example, suppose a researcher's goal is to compare the impact of high education with the impact of not-low education, a more inclusive set, on an outcome. She could use the "dualcal" command to generate *educHI* and *educLO* from the source variable, years of education. The researcher supplies the source variable name, four benchmarks values, and the stem name for the two fuzzy sets (*educ*, in this example).[1]

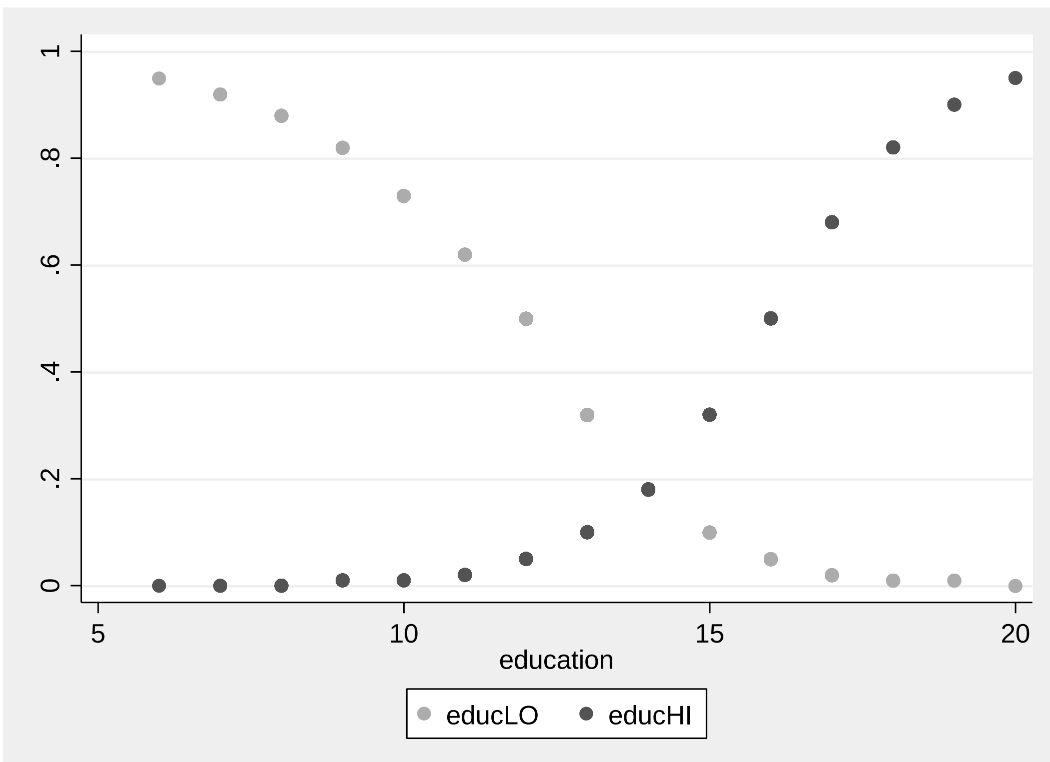
A key focus in using the dualcal command is the specification of the four benchmark values. Notice that in the detailed example presented above the calibration of *highed* uses 12 years as the benchmark for 0.05 membership and 16 years as the benchmark for the cross-over point (0.5). Observe that *lowed* uses these same two benchmark values, only reversed: 12 years is the benchmark value for the cross-over point (0.5), and 16 years is the benchmark value for 0.05 membership. Thus, the same benchmark values can be used in the calibration of two fuzzy sets. The following chart maps the connections between the four benchmark values and fuzzy membership scores in *educHI* and *educLO*:

[1] Of course, it would be necessary to negate *educLO* in order to generate degree of membership in the set of cases with not-low education.

Benchmark	**educHI calibration**	**educLO calibration**
20 years	0.95 (high)	not used
16 years	0.5 (cross-over)	0.05 (not low)
12 years	0.05 (not high)	0.5 (cross-over)
6 years	not used	0.95 (low)

The dualcal command would be executed as follows:
compute educ = dualcal(education,20,16,12,6)
The fuzzy set *educHI* utilizes the first three benchmark values, while *educLO* utilizes the last three benchmark values, in reverse order. The plot of *educLO* and *educHI* against their source variable (*education*) is shown in Figure 3. The fuzzy sets created using this procedure are identical to sets generated using separate commands to produce *lowed* and *highed*, shown previously.

Figure 3: Plot of educLO and educHI Against Years of Education



Discussion

My goal in developing dualcal was to discourage what is probably the most common way of calibrating interval/ratio variables as fuzzy sets. The usual practice is to (1) select a benchmark for high-X, (2) select a benchmark for low-X, and then (3) define the cross-over point in the vicinity of the median or in the vicinity of the midpoint between the high and low benchmarks. The end result is that the not-high benchmark is too low because it has been pegged to the low-X benchmark. Also, the cross-over point for X/not-X, by implication, is also too low. The purpose of dualcal is to encourage users to consider the calibration of high-X and low-X at the same time. In effect, the dualcal procedure forces users to pay attention to the disjuncture of the calibration of high-X versus not-high-X from low-X versus not-low-X.

The dualcal procedure has wide applications; however, it is not always appropriate. For example, the benchmark values for "rich" and "poor" are unlikely to align such that the "not-poor" benchmark coincides with the "rich/not-rich" cross-over point, and the "not-rich" benchmark coincides with the "poor/not-poor" cross-over point. In situations where the benchmarks do not align, the two sets, high-X and low-X, should be calibrated separately.[2]

To specify benchmark values simultaneously for high and low membership in a fuzzy set requires extra effort on the part of researchers. As noted previously, researchers too often rely on a single calibration using three benchmarks and then misconstrue and mislabel the negated set (e.g., as "low" X instead of "not-high" X). When selecting benchmark values using the dualcal procedure, researchers should keep in mind that they are specifying four benchmark values. Ideally, each value selected should have some empirical referent or rationale (Ragin 2008; Ragin and Fiss 2017).

It is best to start with the specification of the benchmark for high membership using relatively strict bounds. That is, the specification of "high" should capture only cases that clearly have full or very close to full membership in the set in question and are clearly well above the benchmark value for not-low. Likewise, the specification of "low" should capture cases that have full or very close to full non-membership in the set in question and are clearly below the benchmark for not-high. When specifying the benchmark value for the cross-over point for membership in "high/not-high," keep in mind that it is also the benchmark for non-membership in "low." When specifying the benchmark for "not-high," keep in mind that it is also the cross-over point for "low/not-low." These restraints on specifying benchmarks have the potential to make calibrations more precise as well as more grounded in evidence.

References

Ragin, Charles C. 2000. *Fuzzy Set Social Science*. Chicago: University of Chicago Press.

Ragin, Charles C. 2008. *Redesigning Social Inquiry: Fuzzy Sets and Beyond*. Chicago: University of Chicago Press.

Ragin, Charles C., and Peer C. Fiss. 2017. *Intersectional Inequality: Race, Class, Test Scores, and Poverty*. Chicago, IL: University of Chicago Press.

---

[2] Thanks go to Claude Rubinson for suggesting this example.