B thinks it will be safe to act in a trusting manner and does so, then A thinks that showed that his or her trusting act paid off and acts trustingly again, and so forth.

It is also possible to interpret the example of trust-building as simultaneous causation. A and B could be working cooperatively on a task that will benefit both, such as sailing a small racing boat that requires simultaneous action by the two people in managing the sails, tending the helm, moving on the deck so as to maintain proper balance, and so on. There trust builds in both persons as the joint action brings success to both. If one waits for the other to show trustworthy action before taking his or her own act, the boat may overturn during the delay.

Simultaneous causation is not, of course, permitted in the S-O-R scheme of things. You might want to squeeze the example of the small boat into figure 4-5 by postulating a sequence in which each S-O-R requires only a split second. If, however, you have sailed in a two-person boat, that sequential explanation will sound very unconvincing. I will offer an explanation I like better in chapter ###.

Additive Correlational Models

A very common assumption in the use of the method of relative frequencies is that the inputs have a simple additive effect on the output. Outside economics, social scientists almost always sort people by levels of multiple variables by using what statisticians call the "additive model." The general form is $y = a + bx_1 + cx_2 + dx_3 + \ldots + mx_n$. In that equation, the x's are the inputs and the y is the output. The equation does not permit multiplicative relations among the x's, nor does it permit triggering relations or step-functions. No procedure of multiple correlation, multiple regression, analysis of variance, or the like can detect any of those latter kinds of relation among variables.

Many sciences make use of mathematical equations to specify predictions. In a science such as physics and in many engineering applications, the strategy is to postulate an equation (a "curve," in the geometric term) and then see how close the observations come to that postulated equation or curve. The curve is not a cloud of points, but a line such that for any value of x there is one and only one value of y. Mathematicians apply the term function to that kind of relation and limit the term to that use, though social scientists use it to mean any kind of nonrandom relation whatever.

In the social sciences, the procedure is the reverse. We collect a cloud of points and then proclaim that the line from which the points have the least mean squared deviation must be the curve we are hunting for. Not only that, we almost always proclaim that the line we are hunting for must necessarily be straight. If the points turn out to be less scattered than chance would leave them, we seem to believe that all those points were trying, so to speak, to array themselves on a straight line but were somehow buffeted or confused by "error." Social scientists use the term "error" to mean any deviation of data from where they hoped the data would fall, regardless of whether the deviation is due to imprecisions of measurement or to effects of unmeasured variables. They believe that the buffeting and confusion is always going on, and that it always occurs in such a way as to produce a cloud of minimum mean squared deviation from where the data-points really wanted to be, so to speak.

If a theory for predicting **y** is expressed as a linear equation such as the additive model, the equation will produce a single value for **y** if every one of the **x**'s is given a value, but for any particular value of **y** there is no unique solution. An infinity of combinations of values of the **x**'s will give that value of **y**. If we fix $\mathbf{x}_1$, then **y** can still take on any value whatsoever, depending on the values of the other **x**'s, and an infinity of values is still available. To put it another way, the equation says only that anything can happen. It is no wonder, then, that we must supply the missing restrictions by making assumptions about "error." We collect data, then calculate the correlations between **y** and each of the **x**'s, and then pretend that the points in the cloud are all really, somehow, on the line **y = a + bx.** We then add in the manner of the additive model all those equations we got from the correlation calculations. We take, let us say, the equations

$$y = a + bx_1$$
$$y = c + dx_2$$
$$y = e + fx_3$$

and add them together:

$$3y = a + c + e + bx_1 = dx_2 + fx_3.$$

Then relabeling the constants to make things prettier, we have

$$y = a + bx_1 + cx_2 + dx_3$$

or the additive model.

If we start out with a theory that postulates a line or curve, not just a nonrandom scatter of points, the theory must include restrictions on the values of the **x**'s. We put on restrictions by using a theory that can give us more than one equation. We need, indeed, as many independent equations as there are **x**'s. To plot a line in 3-dimensional space, for example, suppose out theory allows us to write not only

$$y = 1 + 2x_1 + 3x_2 \quad \text{but also}$$
$$y = 2 + 3x_1 + 4x_2.$$

Solving those equations simultaneously, we get

$$y = -2 - x_1 \quad \text{and}$$
$$y = -1 + x_2.$$

Thus for any single value of x_1 or x_2, we get a single value of **y**. The simultaneous solution also gives us the restriction

$$x_1 = -1 - x_2 \quad \text{or}$$
$$x_2 = -1 - x_1.$$

That restriction tells us the relation between x_1 and x_2. For one particular value of x_1, the theory permits only one particular value of x_2, and vice versa. And for any particular value of x_1 and any corresponding permitted value of x_2, the theory permits only one value of y. Our theory is supported when we test it with data if our values for **y** deviate from the predictions no more than we would expect from the imprecisions of our measuring instruments. Such a theory does not permit deviations due to "unknown variables."

Few theories in social science begin with restrictions on the **x**'s. I will, however, give an example in chapter ###.

D.J. Brown (1975), too, has complained that researchers put too much trust in the additive model. He calls it the "linear model," using "linear" as mathematicians do to indicate that the variables in the equation have no powers higher than one. Brown described six common misuses:

1. Brown says that "the application of this model is obvious for input-output analysis," but when the actual relations among variables may not fit the model, then "application of the model amy actually mislead the researcher" (p. 492).

2. Applications are usually static, with time delays not included in the analysis. One rarely sees, Brown says, a modified version such as $Y_{(t+1)} = a + bX_{(t)}$.

3. Researchers often add more variables to the right side of the equation than is parsimonious, perhaps in the urge to account for as much variance as possible. But when the data are examined by a sub-variety of the model such as analysis of variance, the number of interaction terms grows at a much faster rate than the number of variables, and it soon becomes impossible to make sense of all the interaction terms.

4. "For some reason the aquisition of results which are statistically significant has become of greater importance than results which are strong but not immediately generalizable from a sample to a population in the

statistical sense" (p. 493).

5. ". . . only [when] levels of correlation fall extremely low do some investigators even begin to consider whether their theories may . . . be inaccurate. . . . The lack of conclusiveness on the part of Pearson correlations which are relatively low (.3 to .5) is easily demonstrated by a plot on ordinary graph paper of any two given variables" (pp. 493-494).

6. Researchers too rarely plot correlations graphically. They therefore miss obvious non-linear shapes and outliers. Researchers too often "leave the evaluation to a number generated by the internal workings of a computer and its statistical program" (p. 494).

Brown counted up the numbers of articles reporting Pearson correlations in the _American Educational Research Journal_ from 1970, vol. 7, no. 1 through 1974, vol. 11, no. 2. The percentages per year of articles reporting correlations ranged from 38 to 67. The mean size (positive or negative) of the two-variable correlations in those articles was .27. The percentage of correlations larger (positive or negative) than .90 was a mere 2.

Brown also tabulated all the coefficients of _multiple_ determination (R^2). The mean was .24. Only seven percent were larger than .8. Brown also generated some correlations by using scores taken from a table of random numbers. Applying step-wise regression analysis, R^2 reached

.78 by the fifteenth step even with these randomly generated correlations. "Obviously, the strength of group association [as shown by R^2] is no more impressive than that shown by simple pairs of variables" (p. 496). Brown was saying, in other words, that the researchers reporting in those issues of the American Educational Research Journal could have done as well in predicting **y** from a single **x**, on the average, as they did trying to predict it from multiple **x**'s.

Among other alternatives Brown offers to the linear model are (1) various non-quantitative methods, (2) contingency tables, (3) nonlinear and non-additive relations, (4) extensions of the linear model such as multivariate analysis with more than one dependent variable, path analysis, and factor analysis, (5) models related to the linear model such as linear, dynamic, nonlinear, stochastic, and heuristic programming, and (6) extrapolations and projections. Though he characterizes a few of his alternatives as "non-causal," no place does he offer an alternative to the input-output assumption, and most of his "alternatives" retain the assumption of the single-equation additive model.

Stimuli and Traits

Most of us usually try to explain the behavior of