quarter of that amount, 1 bet for every $10 in your stake! Notice that in a 50/50 game where you win twice the amount that you lose, at an f of .5 you are only breaking even! That means you are only breaking even if you made 1 bet for every $2 in your stake. At an f greater than .5 you are losing in this game, and it is simply a matter of time until you are completely tapped out! In other words, if your f in this 50/50, 2:1 game is .25 beyond what is optimal, you will go broke with a probability that approaches certainty as you continue to play. Our goal, then, is to objectively find the peak of the f curve for a given trading system.

In this discussion certain concepts will be illuminated in terms of gambling illustrations. The main difference between gambling and speculation is that gambling *creates* risk (and hence many people are opposed to it) whereas speculation is a *transference* of an already existing risk (supposedly) from one party to another. The gambling illustrations are used to illustrate the concepts as clearly and simply as possible. The mathematics of money management and the principles involved in trading and gambling are quite similar. The main difference is that in the math of gambling we are usually dealing with Bernoulli outcomes (only two possible outcomes), whereas in trading we are dealing with the entire probability distribution that the trade may take.

BASIC CONCEPTS

A *probability statement* is a number between 0 and 1 that specifies how probable an outcome is, with 0 being no probability whatsoever of the event in question occurring and 1 being that the event in question is certain to occur. An *independent trials process (sampling with replacement)* is a sequence of outcomes where the probability statement is constant from one event to the next. A coin toss is an example of just such a process. Each toss has a 50/50 probability regardless of the outcome of the prior toss. Even if the last 5 flips of a coin were heads, the probability of this flip being heads is unaffected and remains .5.

Naturally, the other type of random process is one in which the outcome of prior events *does* affect the probability statement, and naturally, the probability statement is not constant from one event to the next. These types of events are called *dependent trials processes (sampling without replacement).* Blackjack is an example of just such a process. Once a card is played, the composition of the deck changes. Suppose a new deck is shuffled and a card removed—say, the ace of diamonds. Prior to removing this card the probability of drawing an ace was -4/52 or ,07692307692. Now that mi ace has been drawn from the deck, and not replaced, the probability of drawing an ace on the next draw is 3/51 or .05882352941,

Try to think of the difference between independent and dependent trials processes as simply *whether the probability statement is fixed (independent trials) or variable (dependent trials) from one event to the next based on prior outcomes.* This is in fact the only difference.

THE RUNS TEST

When we do sampling without replacement from a deck of cards, we can determine by inspection that there is dependency. For certain events (such as the profit and loss stream of a system's trades) where dependency cannot be determined upon inspection, we have the runs test. The runs test will tell us if our system has more (or fewer) streaks of consecutive wins and losses than a random distribution.

The runs test is essentially a matter of obtaining the Z scores for the win and loss streaks of a system's trades. A Z score is how many standard deviations you are away from the mean of a distribution. Thus, a Z score of 2.00 is 2.00 standard deviations away from the mean (the expectation of a random distribution of streaks of wins and losses).

The Z score is simply the number of standard deviations the data is from the mean of the Normal Probability Distribution. For example, a Z score of 1.00 would mean that the data you are testing is within 1 standard deviation from the mean. Incidentally, this is perfectly normal.

The Z score is then converted into a *confidence limit,* sometimes also called a *degree of certainty.* The area under the curve of the Normal Probability Function at 1 standard deviation on either side of the mean equals 68% of the total area under the curve. So we take our Z score and convert it to a confidence limit, the relationship being that the Z score is a number of standard deviations from the mean and the confidence limit is the percentage of area under the curve occupied at so many standard deviations.

Confidence Limit (%)	Z Score
99.73	3.00
99	2.58
98	2.33
97	2.17
96	2.05
95.45	2.00
95	1.96
90	1.64

With a minimum of 30 closed trades we can now compute our Z scores. What we are trying to answer is how many streaks of wins (losses) can we expect from a given system? Are the win (loss) streaks of the system we are testing in line with what we could expect? If not, is there a high enough confidence limit that we can assume dependency exists between trades—i.e., is the outcome of a trade dependent on the outcome of previous trades?

Here then is the equation for the runs test, the system's Z score:

(1.01) $Z = (N*(R-.5)-X)/((X*(X-N))/(N-1))$ ^ $(1/2)$

where N = The total number of trades in the sequence.

R = The total number of runs in the sequence.

$X = 2*W*L$

W = The total number of winning trades in the sequence.

L = The total number of losing trades in the sequence.

Here is how to perform this computation:

1. Compile the following data from your run of trades:
   A. The total number of trades, hereafter called N.
   B. The total number of winning trades and the total number of losing trades. Now compute what we will call X. X = 2 * Total Number of Wins * Total Number of Losses.
   C. The total number of runs in a sequence. We'll call this R.

2. Let's construct an example to follow along with. Assume the following trades:

-3, +2, +7, -4, +1, -1, +1, +6, -1, 0, -2, +1

The net profit is +7. The total number of trades is 12, so N = 12, to keep the example simple. We are not now concerned with how *big* the wins and losses are, but rather how *many* wins and losses there are and how many streaks. Therefore, we can reduce our run of trades to a simple sequence of pluses and minuses. Note that a trade with a P&L of 0 is regarded as a loss. We now have:

− + + − + − + + − − − +

As can be seen, there are 6 profits and 6 losses; therefore, X = 2 * 6 * 6

= 72. As can also be seen, there are 8 runs in this sequence; therefore, R = 8. *We define a run as anytime you encounter a sign change when reading the sequence as just shown from left to right* (i.e., chronologically). Assume also that you start at 1.

1. You would thus count this sequence as follows:

−	+	+	−	+	−	+	+	−	−	−	+
1	2		3	4	5	6		7			8

2. Solve the expression:

$N*(R-.5)-X$

For our example this would be:

$12*(8-.5)-72$

$12*7.5-72$

$90-72$

18

3. Solve the expression:

$(X*(X-N))/(N-1)$

For our example this would be:

$(72*(72-12))/(12-1)$

$(72*60)/11$

$4320/11$

392.727272

4. Take the square root of the answer in number 3. For our example this would be:

   392.727272 ^ (1/2) = 19.81734777

5. Divide the answer in number 2 by the answer in number 4. This is your Z score. For our example this would be:

   18/19.81734777 = .9082951063

6. Now convert your Z score to a confidence limit. The distribution of runs is binomially distributed. However, when there arc 30 or more I miles involved, we can use (he Normal Distribution to very closely

approximate the binomial probabilities. Thus, if you are using 30 or more trades, you can simply convert your Z score to a confidence limit based upon Equation (3.22) for 2-tailed probabilities in the Normal Distribution.

The runs test will tell you if your sequence of wins and losses contains more or fewer streaks (of wins or losses) than would ordinarily be expected in a truly random sequence, one that has no dependence between trials. Since we are at such a relatively low confidence limit in our example, we can assume that there is no dependence between trials in this particular sequence.

If your Z score is negative, simply convert it to positive (take the absolute value) when finding your confidence limit. A negative Z score implies positive dependency, meaning fewer streaks than the Normal Probability Function would imply and hence that wins beget wins and losses beget losses. A positive Z score implies negative dependency, meaning more streaks than the Normal Probability Function would imply and hence that wins beget losses and losses beget wins.

What would an acceptable confidence limit be? Statisticians generally recommend selecting a confidence limit at least in the high nineties. Some statisticians recommend a confidence limit in excess of 99% in order to assume dependency, some recommend a less stringent minimum of 95.45% (2 standard deviations).

Rarely, if ever, will you find a system that shows confidence limits in excess of 95.45%. Most frequently the confidence limits encountered are less than 90%. Even if you find a system with a confidence limit between 90 and 95.45%, this is not exactly a nugget of gold. To assume that there is dependency involved that can be capitalized upon to make a substantial difference, you really need to exceed 95.45% as a bare minimum.

As long as the dependency is at an acceptable confidence limit, you can alter your behavior accordingly to make better trading decisions, even though you do not understand the underlying cause of the dependency. If you could know the cause, you could then better estimate when the dependency was in effect and when it was not, as well as when a change in the degree of dependency could be expected.

So far, we have only looked at dependency from the point of view of whether the last trade was a winner or a loser. We are trying to determine if the sequence of wins and losses exhibits dependency or not. The runs test for dependency automatically takes the percentage of wins and losses into account. However, in performing the runs test on runs of wins and losses, we have accounted for the *sequence* of wins and losses but not (heir *size.* In order to have true independence, not only must the sequence of the wins and losses be independent, the sizes of the wins and losses within the

sequence must also be independent. It is possible for the wins and losses to be independent, yet their sizes to be dependent (or vice versa). One possible solution is to run the runs test on only the winning trades, segregating the runs in some way (such as those that are greater than the median win and those that are less), and then look for dependency among the size of the winning trades. Then do this for the losing trades.

SERIAL CORRELATION

There is a different, perhaps better, way to quantify this possible dependency between the size of the wins and losses. The technique to be discussed next looks at the sizes of wins and losses from an entirely different perspective mathematically than the does runs test, and hence, when used in conjunction with the runs test, measures the relationship of trades with more depth than the runs test alone could provide. This technique utilizes the linear correlation coefficient, r, sometimes called *Pearson's r*, to quantify the dependency/independency relationship.

Now look at Figure 1-2. It depicts two sequences that are perfectly correlated with each other. We call this effect *positive correlation.*

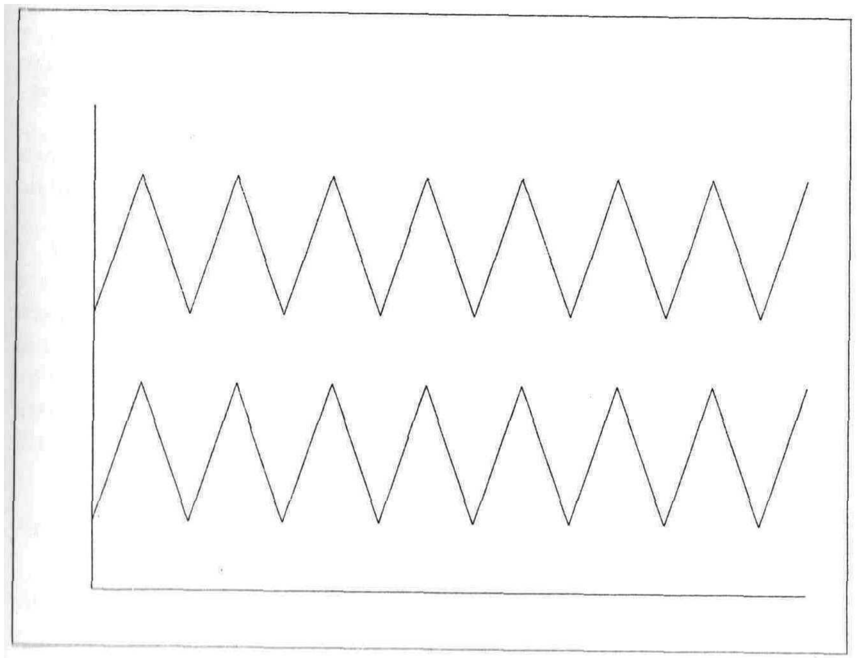

Figure 1–2 Positive correlation (r = +1.00).