A Probability Model of Accuracy in Deception Detection Experiments

Hee Sun Park and Timothy R. Levine

This essay extends the recent work of Levine, Park, and McCornack (1999) on the veracity effect in deception detection. The probabilistic nature of a receiver's accuracy in detecting deception is explained, and a receiver's detection of deception is analyzed in terms of set theory and conditional probability. Detection accuracy is defined as intersections of sets, and formulas are presented for truth accuracy, lie accuracy, and total accuracy in deception detection experiments. In each case, accuracy is shown to be a function of the relevant conditional probability and the truth-lie base rate. These formulas are applied to the Levine et al. results, and the implications for deception research are discussed. **Key words:** Accuracy, Deception

Researchers have long been interested in deception detection. Literature reviews conclude that an individual's accuracy in detecting a lie is slightly above a chance (e.g., Anderson, Ansfield & DePaulo, 1997; Kalbfleisch, 1994; Miller & Stiff, 1993). Consistent with this conclusion, meta-analysis shows that people tend to be about 57% accurate (Kraut, 1980) when accuracy is calculated by averaging across truths and lies and when an equal number and lies are judged (Levine, Park, & McCornack, 1999).

Researchers have also sought to find factors that affect detection accuracy. For example, training (deTurk & Miller, 1990; Fieldler & Walka, 1993), familiarity (Feeley, deTurck, & Young, 1995), and receiver suspicion (McCornack & Levine, 1990) affect peoples' ability to distinguish truths from lies. Although these and other factors significantly impact detection accuracy, accuracy rates seldom drop below 40% or exceed 70% in detection experiments (Kalbfleisch, 1994; Miller & Stiff, 1993).

Levine et al. (1999) question the conclusions drawn from previous detection accuracy studies. Levine et al. show that because people are most often truth-biased, only truth accuracy is above chance, and that lie accuracy is typically below chance levels.[1] Truth and lie accuracy are not correlated, and the effects of external variables (e.g., familiarity, suspicion, probing) are often not general across truth and lie accuracy. An individual's accuracy in detecting lies is also contingent the ratio of lies to the total number of statements judged (i.e., the truth-lie base rate). These findings challenge several previously and widely held beliefs about deception detection including the belief that humans can detect deception at slightly above chance levels. In short, Levine et al. argue that the results of previous research are artifacts of reporting average accuracy based on a common and artificially set truth-lie base rate. They contend that truth and lie accuracy need to be estimated separately, and that researchers should consider base rates before drawing conclusions about accuracy rates.

Hee Sun Park (M.A., University of Hawaii, 1998) is a doctoral student in the Department of Communication at the University of California at Santa Barbara. Timothy R. Levine (Ph.D. Michigan State University, 1992) is Associate Professor of Communication at Michigan State University.

Communication Monographs, Vol. 68, No. 2, June 2001, pp 201–210

This essay extends Levine et al.'s work on the veracity effect by examining detection accuracy as an issue of probability. Based on set theory and the concept of conditional probability, we explain Levine et al.'s findings with probability formulas. Our formulas show why truth accuracy and lie accuracy diverge. This analysis also explains why the truth-lie base rate is a crucial factor in accuracy rates.

In order to model detection accuracy, we describe the type of experiment we are modeling, and articulate the assumptions of our model. Next, set theory and conditional probability are explained, and shown to apply to detection accuracy experiments. Formulas for lie detection, truth detection, and total accuracy are presented and explicated. Examples are provided, and the implications for deception research are discussed. Our effort to model detection accuracy begins with a brief presentation of relevant definitions.

The Model

Definitions

Although deception is defined in a variety of ways, deception may be defined most simply as when a person knowingly misleads another person (Levine, 1994). A lie is one type of deceptive message, and for the purpose of this paper, a lie is defined as a message that is known by the message source to be false, but is presented as if it were true.

The detection of a lie involves at least two parties. A source produces a message that has some probability of being a lie. A message receiver judges the veracity of the message presented. A message receiver may be said to be accurate when a truthful message is judged as truthful, or when a lie is judged as a lie. The former situation is labeled truth accuracy and the latter situation refers to lie accuracy. Truthful messages judged as lies, or lies judged as truths are considered inaccurate judgments. Total, or average accuracy refers to ratio the judgments that are accurate, regardless of veracity, to the total number of judgments made. Thus, we define accuracy as hit rate (Wagner, 1993).

The Typical Deception Detection Experiment

Although there is a large literature on deception detection accuracy, the vast majority of experiments use variations on the same basic experimental design (Miller & Stiff, 1993). In the typical experiment, one group of participants is recruited to serve as message sources. Sources are either instructed or induced to either lie or tell the truth, or both. A different group of participants are recruited to judge the honesty of the sources' messages. Judges are typically exposed to a number of messages where half of the messages are true, and the other half are lies. Each message is judged as either honest or a lie. Accuracy is then calculated as the proportion of correct truth-lie judgments to total judgments. As mentioned above, the average accuracy rate in these experiments is 57% when the truth-lie base rate is .50.

Assumptions

All mathematical models require assumptions, and our model makes three key assumptions. First, we assume that the messages being judged fall into one of two mutually exclusive and exhaustive categories. The messages presented by sources are either truths or lies. Further, in a given experiment, there is a known proportion, set in advance by the researcher, of messages that are lies. Second, our model assumes that veracity judgments are also dichotomous. Receivers are assumed to judge messages as either truths or lies. Third, we assume that it is possible to know the probability of the receiver judgment given the veracity of a source's message, but the probability that source's message is a truth (or lie) given a receiver's judgment is unknowable and irrelevant.

While these assumptions may not reflect reality in all contexts, they accurately reflect the type of deception detection experiment we are modeling. In such experiments, both messages and the judgments made regarding those messages are dichotomous. Also, in detection experiments, the veracity of source messages precedes receiver evaluations and is under the control of the researcher.

Sets, Sample Space and Basic Probability Theory

The most basic concepts in modern probability theory include sample space, elementary events, and events (i.e., sets, classes or event classes). The sample space refers to the set of all possible outcomes of some well defined act or process. An elementary event refers to individual outcomes, while events are sets or classes of elementary events (Freund, 1973; Hays, 1994). Upper case letters are conventionally used to symbolize events, and the probability of some event in the sample space is marked with P. Thus, the probability of event A is written as P(A).

In deception detection experiments, receivers are exposed to a series of messages, some of which are true and some of which are lies. In such situations, truths and lies may be thought of as sets or events, each comprised of individual messages (the elementary events), and each being a subset in the sample space (the set of all possible messages). If we use T to denote truthful messages, the probability that a given message is true is P(T). P(T) represents the base rate in deception experiments. As noted above, P(T) is almost always set at .5 in deception research.

We can also think of receiver judgments as sets. Receivers make a series of judgments, sometimes judging a message as true, and other times labeling it a lie. Here, truth and lie judgments may be thought of as sets or events, each comprised of individual judgments of a specific message (the elementary events), and each being a subset in the sample space. If H represents all messages that are judged as honest, the probability that a receiver will judge a message as honest is P(H). The reader should note that P(H) is often referred to as truth-bias in the literature, because P(H) is almost always found to be greater than .5.

Truth and Lie Detection as Joint Events

If there are two events, A and B, these events may jointly occur. There are two types of joint events. The first type of joint event is when an outcome is a member of both event A and event B. The joint event A and B uses the symbol $\cap$, which means intersection. Thus, the joint event $A \cap B$ is read as the intersection of sets A and B, and refers to an outcome that is a member of both individual events. For example, if A refers to all people who are adults, and B refers to all people with brown eyes, $A \cap B$ refers to all adults with brown eyes.

The second type of joint event is a union, which is symbolized as $\cup$. $A \cup B$ stands for A or B. For example, if A refers to all people who are adults, and B refers to all people with brown eyes, $A \cup B$ refers to all people who are adults or have brown eyes.

The compliment of event A is an outcomes that is not A. Not A is symbolized $\sim$A. In the example above, all people who are not adults are $\sim$A. Because truths and lies are dichotomous in the experiments we are modeling, lies are the compliment of truths, and lie judgments are the compliment of truth judgments.

The detection of a truthful message may be thought of as an intersection. If messages that are truthful are event T, and messages that are judged as truthful are event H, the event $T \cap H$ is a truth that is correctly identified as truthful. That is, truth accuracy occurs when a message is both truthful, and judged as truthful by a receiver. The probability that a truthful messages will be judged as truthful can be written $P(T \cap H)$.

Lies are messages that are not truthful and might be symbolized as $\sim$T. So, if $\sim$T denotes a lie, and $\sim$H stands for messages that are judged as lies, then an accurately detected lie is the intersection of $\sim$T and $\sim$H (i.e., $\sim T \cap \sim H$). Here, the probability that a lie is judged correctly may be symbolized as $P(\sim T \cap \sim H)$. The intersections of $\sim T \cap H$ (lies judged as honest) and $T \cap \sim H$ (i.e., truths judged as lies) are erroneous judgments. Thus, $P(\sim T \cap H)$ and $P(T \cap \sim H)$ reflect the probabilities of incorrect judgments.

Total accuracy may be thought of as a union of truth accuracy and lie accuracy. When someone is accurate in detecting deception, we usually mean that they either correctly identified a truth or a lie. If correctly identifying a truth is $(T \cap H)$ and correctly identified lies is $(\sim T \cap \sim H)$, then a correct veracity judgment is $(T \cap H) \cup (\sim T \cap \sim H)$. Because the two types of accuracy are mutually exclusive, the probability of a correct judgment is $P(T \cap H) + P(\sim T \cap \sim H)$.

Conditional Probability

Another way to think of the probability of detecting a truth or a lie is in terms of conditional probability. For instance, we might ask, given that a source is lying, what is the probability that the receiver will judge the message as a lie? The conditional probability of event A given condition B is denoted $P(A \mid B)$.

Mathematically, the conditional probability of event A given event B in sample space S is $P(A \mid B) = P(A \cap B) \div P(B)$ where $P(B) \neq 0$. That is, the probability of event A occurring given that event B has already occurred is the probability of both A and B occurring divided by the probability of B.

If we solve for $P(A \cap B)$ in the equation above, we find that $P(A \cap B) = P(A \mid B) \times P(B)$. Here, the probability of the joint event A and B is equal to the conditional probability of A given B multiplied by the probability of event B. Freund (1973) refers to this derivation as the general rule of multiplication. Note also that if $P(B) = 1.00$, then $P(A \cap B) = P(A \mid B)$.

Probability Formulas for Truth and Lie Detection

Above, we conceptualized accuracy as an intersection of two sets. Let T be truthful messages and $\sim$T represent lies. Further, let H be honesty judgments and $\sim$H be lie judgments. Then an accurate truth judgment is $T \cap H$ and the probability of a correct truth judgment is $P(T \cap H)$. Symbolically, $\sim T \cap \sim H$ is a correctly identified lie, and $P(\sim T \cap \sim H)$ is the probability that a lie will be correctly identified. Recall also that we assumed that judgments depend on source veracity but not vice versa. That is, H is conditional on T, but T given H is unknown.

Applying the general rule of multiplication, the probability that a truth will be correctly judged is

$$P(T \cap H) = P(H \mid T) \times P(T) \qquad \text{Formula 1}$$

The probability that a lie is identified correctly is

$$P(\sim T \cap \sim H) = P(\sim H \mid \sim T) \times P(\sim T) = P(\sim H \mid \sim T) \times 1 - P(T) \qquad \text{Formula 2}$$

And total accuracy is

$$P(T \cap H) + P(\sim T \cap \sim H) \qquad \text{Formula 3}$$

Two Factors Determining Detection Accuracy

As can be seen from the formula above, detection accuracy depends on two distinct factors. The first factor that determines accuracy is the conditional probability. This is the probability that a truth judgment is made given that a message is truthful, or the probability that a lie judgment is rendered give that the message is a lie. The second factor is what we have called the truth-lie base rate. This is the probability that a given message is a truth or a lie. Each is discussed in turn.

The Conditional Probability

Conditional probability and accuracy are easily confused. Recall that we defined accuracy as the intersections of sets. For example, truth accuracy was defined as ($T \cap H$) which represents all truthful messages that are judged as truthful. However, researchers usually use the conditional probability to estimate truth and lie accuracy when calculating separate truth and lie accuracy scores. That is, truth accuracy is calculated by dividing the number of correct truth judgments by the total number of truth judgments. In such calculations, P(T) is set at 1.00 because the calculation only considers messages that are truthful (i.e., the sample space is limited to truthful messages). Recall that $P(A \mid B) = P(A \cap B)$ if and only if $P(B) = 1.00$. Thus, truth accuracy as most often calculated is an intersection of sets, but it is strictly limited to the condition where all messages are true.

Estimates of the conditional probabilities obtained in previous research are remarkably stable. In Levine et al.'s (1999) studies, the conditional probabilities for truths ranged from .686 to .879 ($M = .779$) and the conditional probabilities for lies ranged from .225 to .525 ($M = .349$). Examination of the literature shows that estimates almost always fall with these ranges. Experiments using unsanctioned lies (e.g., Stiff & Miller, 1986), face-to-face interaction (e.g., Buller et al., 1991b), and studies that do not prime receivers to expect deception (e.g., McCornack & Levine, 1990) each provide estimates within the ranges reported above.

Research suggests that the strongest single determinant of the conditional probabilities is truth-bias, which we denoted P(H) or $1 - P(\sim H)$. Truth-bias or P(H) might be thought of as an "unconditional probability" in that it is typically defined conceptually (e.g., Anderson et al., 1997) and operationally (e.g., McCornack & Parks, 1986; Levine et al., 1999) as the number of truth judgments regardless of actual message veracity. Levine et al. (1999) found that the uncorrected correlations between truth-bias and the conditional probability for truth ranged from .50 to .66, while for lies the correlations ranged from −.75 to −.82.

Variables that affect the conditional probabilities and hence accuracy may affect the conditional probabilities directly or indirectly through truth-bias. That is, any

Table 1
PREDICTING ACCURACY FOR DIFFERENT BASE-RATES

P(T)	Type of Accuracy	Calculation	Accuracy Estimate
P(T) = .10	Truth Accuracy	.779 × .10 =	.0779
	Lie Accuracy	.349 × .90 =	.3141
	Total Accuracy	.0779 + .3141 =	.3920
P(T) = .25	Truth Accuracy	.779 × .25 =	.1948
	Lie Accuracy	.349 × .75 =	.2618
	Total Accuracy	.1948 + .2618 =	.4567
P(T) = .50	Truth Accuracy	.779 × .50 =	.3895
	Lie Accuracy	.349 × .50 =	.1745
	Total Accuracy	.3895 + .1745 =	.5640
P(T) = .75	Truth Accuracy	.779 × .75 =	.5843
	Lie Accuracy	.349 × .25 =	.0872
	Total Accuracy	.5843 + .0872 =	.6715
P(T) = .90	Truth Accuracy	.779 × .90 =	.7011
	Lie Accuracy	.349 × .10 =	.0349
	Total Accuracy	.7011 + .0349 =	.7360

variable that affects P(H) should also indirectly affect P(H | T) while other variables may impact P(H | T) directly. Further efforts to model the conditional probabilities will need to specify such effects.

The Base-Rate

The second factor that determines accuracy in our equations is the truth-lie base rates which were symbolized as P(T) or P(~T). The base rates refer to the probabilities that a message is a truth or a lie. In almost all accuracy studies there is a 50-50 chance that a message is a lie. Thus, P(T) = P(~T) = 0.50. However, when truth accuracy is calculated, P(T) = 1.00, and P(~T) = 1.00 when lie accuracy is calculated.

The base-rate component in detection accuracy has generally been ignored in previous research (Levine et al., 1999). Yet as our formula show, base-rates are a crucial factor in determining accuracy, and the point estimates obtained in studies using a single common base rate will not generalize to other base-rates. The example below shows how the use of the common .50 base rate led to the often cited across-study accuracy rate of .57.

In the typical study, P(T) and P(~T) are set at .50. Recall that the average conditional probabilities from Levine et al. (1999) were P(H | T) = .779 and P(~H | ~T) = .349 and that these were typical of estimates reported in the literature. Applying our formulas, the probability that a truthful message is judged as honest is .779 × .50 = .3895, and the probability of a lie being judged a lie is .349 × .50 = .1745. Total accuracy using these estimates is then the sum of truth accuracy and lie accuracy, or .3895 + .1745 = .564, a result almost identical to the across study average of .57. Alternatively, because P(T) and P(~T) = .50, we can calculate total accuracy by averaging truth accuracy and lie accuracy, i.e. (.779 + .349) ÷ 2 = .564.

Obviously, different results would be obtained for different base rates. In Table 1, truth, lie, and total accuracy are calculated for five different base-rates (.10, .25, .50, .75, and .90) using the conditional probabilities employed above. Estimates of total accuracy range from 39.2% when 90% of the messages are lies to 73.6% when 90% of the messages are honest. Even more dramatic effects can be seen on the estimates of truth and lie accuracy. The probabilities of correctly judging a lie range from .035 to

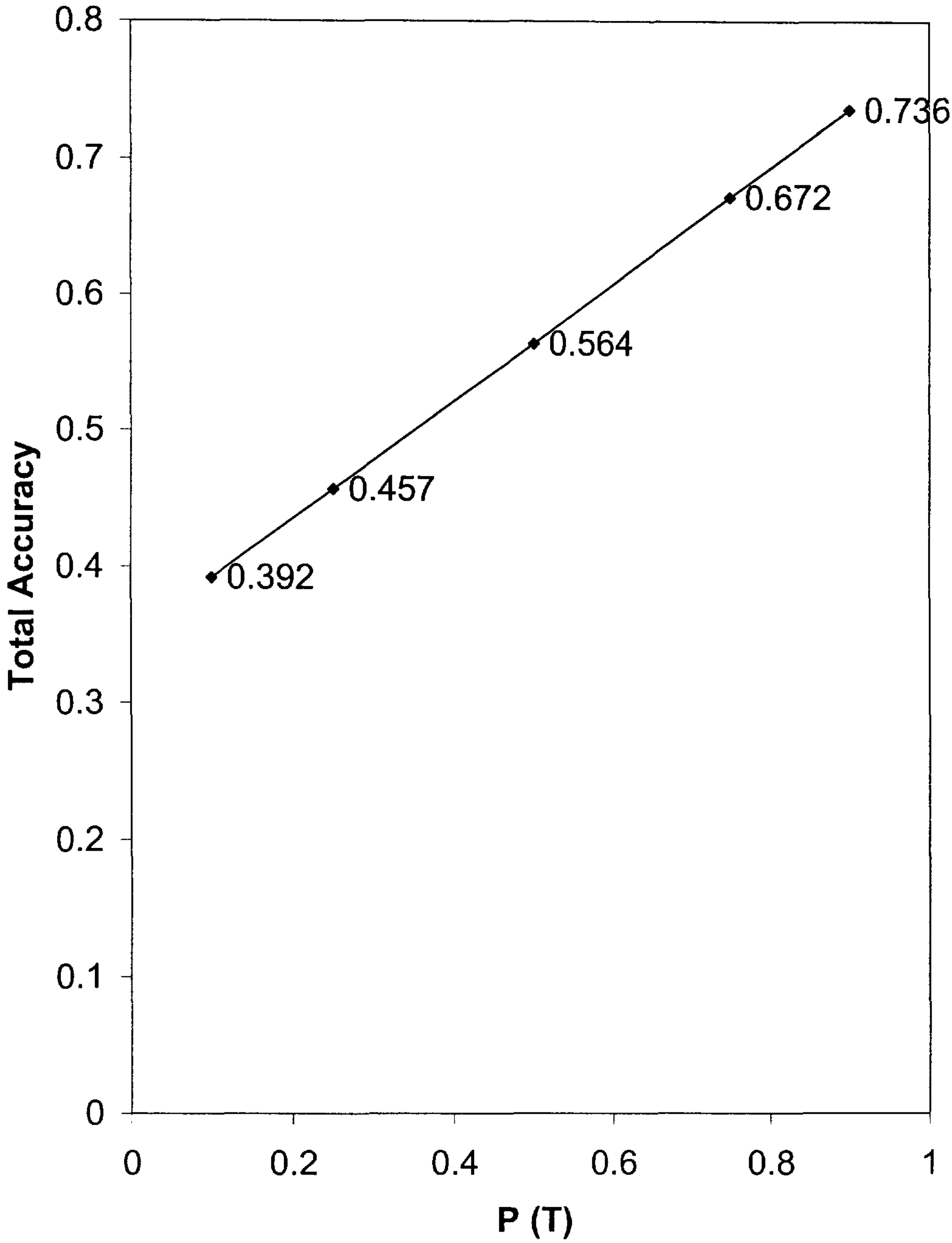

FIGURE 1
THE PREDICTED LINEAR EFFECTS OF BASE-RATE ON TOTAL ACCURACY.

.314 while the probabilities for truths range from .078 to .701 depending on the base rate.

In figure 1, base rate is plotted onto predicted total accuracy. Consistent with Levine et al.'s (1999) findings, the relationship between total accuracy and base rate is positive and linear. The slope and the y-intercept of the line will vary from study to study depending on conditional probabilities for truths and lies, but our formulas predict that the relationship will remain linear. Because receivers are almost always truth-biased, the conditional probability for truth is greater than the conditional probability for lies, and the relationship between based-rate and accuracy is positive.

As repeatedly noted, previous studies have artificially set the base rate at .50. One might question how applicable this rate is to nonresearch settings. Research on the prevalence of lies in everyday life is sparse and the results vary. For example, Turner, Edgely and Olmstead (1975) reported that some form of information control was evident in the majority of conversational statements. While not all instances of information control qualify as deception, Turner et al.'s results are often interpreted as evidence that deception is common in everyday conversation. Perhaps then the base-rates employed in detection experiments are not that different normal conversation.

Very different conclusions, however, can be drawn from DePaulo, Kashy, Kirkendon, & Epstein's (1996) diary studies of lies. DePaulo et al. found that people reporting telling, on average, only one to two lies per day. Given the number of statements people make during the course of a typical day, these results suggest that only a very small proportion statements in everyday conversations are lies. If few conversational statements are lies, our formulas show that the probability of detecting an infrequent lie is low. For example, if only one out of one hundred statements are lies and if the conditional probability of detecting a lie is .35, then the probability of detecting a lie would be $p = .0035$.

There is of course no definitive answer to the question of the actual base-rate in the typical everyday conversation. The likelihood of deceit surely varies dramatically across people and situations. Whatever the base-rate, however, the results of studies using a single base rate should not be generalized beyond that base rate. Our formulas, however, are useful in predicting what accuracy would be at different base rates.

Discussion

Limitations

A number of limitations in our model exist, and these stem from the our relatively modest goals. First, we attempted to model a specific sort of detection accuracy experiment where accuracy is calculated and interpreted in terms of a percent of agreement. Viewing accuracy as an intersection of sets, and viewing lies as the compliment of truths requires a dichotomous view of deception, and hence our model was not intended to apply to studies of accuracy using continuous measures. Similarly, because we modeled accuracy as hit-rate, our model is not intended to control for chance agreement attributable to perceiver bias (cf. Wagner, 1993). Modifications or extensions to our model would be required before our formulas could be applied to continuous view of deception or models of chance agreement.

Another limitation in our probability model is that conditional probabilities are treated as givens in our formulas. Conditional probabilities will vary to some extent from study to study depending on the extent of truth-bias, deceiver's ability, and detector's ability. These variations are not modeled directly in the current formula. Thus, the accuracy rates predicted by our formulas will only be as accurate as the estimates of conditional probabilities used to make the estimates. More research is needed in order to model conditional probabilities.

Conclusion

This essay extends Levine et al.'s (1999) work on the veracity effect by specifying a probability model of accuracy in deception detection. Accuracy was conceptualized as an intersection of sets, and shown to be a function of the relevant conditional probability and base-rate. This model contributes to our understanding of deception detection in a number of ways. The formulas presented here predict the 57% across-study accuracy rate evident in the literature based on truth and lie-accuracy and the .50 base-rate used in previous studies. The model makes explicit the meaning of truth and lie accuracy in relation to total accuracy. Our formulas show why base-rate is an essential component is estimates of accuracy, and they predict the linear relationship between base-rate and accuracy observed in previous research. Finally, our model show how overall accuracy is a function of truth accuracy, lie accuracy, and base-rate, and allow researchers to predict overall difference in overall accuracy based on the values of these three critical components.

Notes

[1]These conclusions depend on what is meant by chance and accuracy. The conclusion that truth accuracy is above chance and lie accuracy is below chance are based on comparisons of hit rate to an objective base-rate. So, as long as people are truth-biased, they are more likely to guess correctly when the statement being judged is a truth as opposed to a lie. As Wagner (1993) points out, however, different views of accuracy and chance might yield different conclusions. For example, the greater levels of raw accuracy (hit rate) for truths than lies may be explainable entirely in terms of chance because judges simply guess true more often (i.e., they are truth-biased). In this sense, truth accuracy may not be greater than chance. This paper focuses on modeling raw accuracy or hit rate because that is what is reported in the deception literature. If our question was whether people are more accurate in detecting truths and less accurate at detecting lies simply because they are truth biased, then we would use an approach like that of Wagner (1993) which corrects accuracy rates for judges' bias.

References

Anderson, D. E., Ansfield, M. E., & DePaulo, B. M. (1997). Love's best habit: Deception in the context of relationships. In P. Philippot, R. S. Feldman, & E. J. Coats (Eds.) *The social context of nonverbal behavior* (pp. 372–409). Cambridge: Cambridge University Press.

Buller, D. B., Strzyzewski, K. D., & Hunsaker, F. G. (1991). Interpersonal deception II: The inferiority of conversational participants as deception detectors. *Communication Monographs, 58,* 1–24.

DePaulo, B. M., Kashy, D. A., Kirkendol, M. M., & Epstein, J. A. (1996). Lying in everyday life. *Journal of Personality and Social Psychology, 70,* 979–995.

deTurck, M. A., & Miller, G. R. (1990). Training observers to detect deception: Effects of self-monitoring and rehearsal. *Human Communication Research, 16,* 603–620.

Feeley, T. H., deTurck, M. A., & Young, M. J. (1995). Baseline familiarity in lie detection. *Communication Research Reports, 12,* 160–169.

Freund, J. E. (1993). *Introduction to probability.* NY: Dover.

Fiedler, K., & Walka, I. (1993). Training lie detectors to use nonverbal cues instead of global heuristics. *Human Communication Research, 20,* 199–223.

Kalbfleisch, P. J. (1994). The language of detecting deceit. *Journal of Language and Social Psychology, 13,* 469–496.

Kraut, R. (1980). Humans as lie detectors. *Journal of Communication, 30,* 209–216.

Hays, W. L. (1994). *Statistics.* Fort Worth, TX: Harcourt Brace.

Levine, T. R. (1994, November). *Conceptualizing interpersonal and relational deception.* Presented at the annual meeting of the Speech Communication Association, New Orleans, LA.

Levine, T. R., Park, H. S., & McCornack, S. A. (1999). Accuracy in detecting truths and lies: Documenting the "veracity effect." *Communication Monographs, 66,* 125–144.

McCornack, S. A. (1997). The generation of deceptive messages: Laying the groundwork for a viable theory of interpersonal deception. In J. O. Greene (Ed.). *Message production* (pp. 91–126). Mahwah, NJ: LEA.

McCornack, S. A., & Levine, T. R. (1990). When lovers become leery: The relationship between suspicion and accuracy in detecting deception. *Communication Monographs, 57,* 219–230.
McCornack, S. A., & Parks, M. R. (1986). Deception detection and relationship development: The other side of trust. In M. L. McLaughlin (Ed.) *Communication yearbook 9* (pp. 377–389). Beverly Hills, CA: Sage.
Miller, G. R., & Stiff, J. B. (1993). *Deceptive communication.* Newbury Park, CA: Sage.
Stiff, J. B., & Miller, G. R. (1986). "Come to think of it. . .": Interrogative probes, deceptive communication, and deception detection. *Human Communication Research, 12,* 339–357.
Turner, R. E., Edgley, C., & Olmsteead, G. (1975). Information control in conversations: Honesty is not always the best policy. *Kansas Journal of Sociology, 11,* 69–89.
Wagner, H. L. (1993). On measuring performance in category judgment studies of nonverbal behavior. *Journal of Nonverbal Behavior, 17,* 3–28.
Zuckerman, M., DePaulo, B. M., & Rosenthal, R. (1981). Verbal and nonverbal communication of deception. In L. Berkowitz (Ed.), *Advances in experimental social psychology* (Vol. 14, pp. 1–59). New York: Academic Press.

Received: December 7, 2000
Accepted: February 1, 2001