Why do Nigerian Scammers Say They are from Nigeria?

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ABSTRACT

False positives cause many promising detection technologies to be unworkable in practice. Attackers, we show, face this problem too. In deciding who to attack true positives are targets successfully attacked, while false positives are those that are attacked but yield nothing.

This allows us to view the attacker's problem as a binary classification. The most profitable strategy requires accurately distinguishing viable from non-viable users, and balancing the relative costs of true and false positives. We show that as victim density decreases the fraction of viable users than can be profitably attacked drops dramatically. For example, a 10× reduction in density can produce a 1000× reduction in the number of victims found. At very low victim densities the attacker faces a seemingly intractable Catch-22: unless he can distinguish viable from non-viable users with great accuracy the attacker cannot find enough victims to be profitable. However, only by finding large numbers of victims can he learn how to accurately distinguish the two.

Finally, this approach suggests an answer to the question in the title. Far-fetched tales of West African riches strike most as comical. Our analysis suggests that is an advantage to the attacker, not a disadvantage. Since his attack has a low density of victims the Nigerian scammer has an over-riding need to reduce false positives. By sending an email that repels all but the most gullible the scammer gets the most promising marks to self-select, and tilts the true to false positive ratio in his favor.

1. INTRODUCTION: ATTACKERS HAVE FALSE POSITIVES TOO

False positives have a long history of plaguing security systems. They have always been a challenge in behavioral analysis, and anomaly and intrusion detection [5]. A force-fed diet of false positives have habituated users to ignore security warnings [15]. In 2010 a single false positive caused the McAfee anti-virus program to send millions of PC's into never-ending reboot cycles. The mischief is not limited to computer security. Different fields have different names for the inherent trade-offs that classification brings. False alarms must be balanced against misses in radar [22], precision against recall in information retrieval, Type I against Type II errors in medicine and the fraud against the insult rate in banking [19]. Common to all of these areas is that one type of error must be traded off against the other. The relative costs of false positives and false negatives changes a great deal, so no single solution is applicable to all domains. Instead, the nature of the solution chosen depends on the problem specifics. In decisions on some types of surgery, for example, false positives (unnecessary surgery) are preferable to false negatives (necessary surgery not performed) since the latter can be far worse than the former for the patient. At the other extreme in deciding guilt in criminal cases it is often considered that false negatives (guilty person goes free) are more acceptable than false positives (innocent person sent to jail). In many domains determining to which of two classes something belongs is extremely hard, and errors of both kinds are inevitable.

Attackers, we show, also face this trade-off problem. Not all targets are viable, *i.e.*, not all yield gain when attacked. For an attacker, false positives are targets that are attacked but yield nothing. These must be balanced against false negatives, which are viable targets that go un-attacked. When attacking has non-zero cost, attackers face the same difficult trade-off problem that has vexed many fields. Attack effort must be spent carefully and too many misses renders the whole endeavor unprofitable.

Viewing attacks as binary classification decisions allows us to analyze attacker return in terms of the Receiver Operator Characteristic (ROC) curve. As an attacker is pushed to the left of the ROC curve social good is increased: fewer viable users and fewer total users are attacked. We show that as the density of victims in the population decreases there is a dramatic deterioration in the attacker's return. For example, a 10× reduction in density can causes a much greater than 1000× reduction in the number of viable victims found. At very low victim densities the attacker faces a seemingly intractable Catch-22: unless he can distinguish viable from non-viable users with great accuracy the attacker cannot find enough victims to be profitable. However, only by finding large numbers of victims can he learn how to accurately distinguish the two. This suggests, that at low enough victim densities many attacks pose no economic threat.

Finally, in Section 4, we offer a simple explanation for the question posed in the title, and suggest how false positives may be used to intentionally erode attacker economics.

2. BACKGROUND

2.1 Attacks are seldom free

Malicious software can accomplish many things but few programs output cash. At the interface between the digital and physical worlds effort must often be spent. Odlyzko [3] suggests that this frictional interface between online and off-line worlds explains why much potential harm goes unrealized. Turning digital contraband into goods and cash is not always easily automated. For example, each respondent to a Nigerian 419 email requires a large amount of interaction, as does the Facebook "stuck in London scam." Credentials may be stolen by the millions, but emptying bank accounts requires recruiting and managing mules [7]. The endgame of many attacks require per-target effort. Thus when cost is non-zero each potential target represents an investment decision to an attacker. He invests effort in the hopes of payoff, but this decision is never flawless.

2.2 Victim distribution model

We consider a population of N users, which contains M viable targets. By viable we mean that these targets always yield a net profit of G when attacked, while non-viable targets yield nothing. Each attack costs C; thus attacking a non-viable target generates a loss of C. We call $d = M/N$ the density of viable users in the population.

We assume that some users are far more likely to be viable than others. Viability is not directly observable: the attacker doesn't know with certainty that he will succeed unless he tries the attack. Nonetheless, the fact that some users are better prospects than others is observable. We assume that the attacker has a simple score, x, that he assigns to each user. The larger the score, the more likely in the attacker's estimate the user is to be viable.

More formally, the score, x, is a sufficient statistic [22]. The attacker might have several observations about the user, where he lives, his place of work, the accounts he possesses, *etc*: all of these be reduced to the single numeric quantity x. This encapsulates all of the *observable* information about the viability of User(i). Without loss of generality we'll assume that viable users tend to have higher x values than non-viable ones. This does not mean that all viable users have higher values that non-viable ones. For example, we might have $pdf(x \mid \text{non-viable}) = \mathcal{N}(0, 1)$ and $pdf(x \mid \text{viable}) = \mathcal{N}(\mu, 1)$. Thus, the observable x is normally distributed with unit variance, but the mean, μ, of x over viable users is higher than over non-viable users. An example is shown in Figure 2.

The viability depends on the specific attack. For example, those who live in wealthier areas may be judged more likely to be viable under most attacks. Those who are C-level officers at large corporations might be more viable of elaborate industrial espionage or Advanced Persistent Threat attacks, *etc.* Those who have fallen for a Nigerian scam, may be more likely to fall for the related "fraud funds recovery" scam.

It is worth emphasizing that rich does not mean viable. There is little secret about who the richest people in the world are, but attacking the Forbes 100 list is not a sure path to wealth. To be viable the attacker must be able to successfully extract the money (or other resource he targets). For example, if an attacker gets keylogging malware on a user's machine, harvests banking passwords but cannot irreversibly transfer money from the account this counts as a failure not a success. This is a cost to the attacker for no gain.

2.3 Attack model

For now we assume a single attacker. He decides whether to attack User(i) based on everything he knows about how likely User(i) is to be viable, *i.e.*, based on his observation of x_i. His expected return from attacking a user with observable x_i is:

$$P\{\text{viable} \mid x_i\} \cdot G - P\{\text{non-viable} \mid x_i\} \cdot C.$$

Clearly, the best case for the attacker is to attack if $P\{\text{viable} \mid x_i\} \cdot G > P\{\text{non-viable} \mid x_i\} \cdot C$. He can never do better, but can easily do worse. The attacker does not of course know $P\{\text{viable} \mid x_i\}$; he generally estimates it from his previous experience. The particular problem that this poses when victim density is low is explored in Section 3.7.

In an attack campaign the true positive rate, t_p, is the fraction of viable targets attacked, and the false positive rate, f_p is the fraction of non-viable targets attacked. That is, t_p is the number of viable users attacked divided by the total number of viable users. Similarly, f_p is the number of non-viable users attacked divided by the total number of non-viable users. Thus the attacker will attack $d \cdot t_p \cdot N$ viable users and $(1-d) \cdot f_p \cdot N$ non-viable users. The expected return is then:

$$E\{R\} = (d \cdot t_p \cdot G - (1-d) \cdot f_p \cdot C) \cdot N. \qquad (1)$$

Our attacker risks two types of errors. Sometimes he will attack a non-viable user and gain nothing (thereby losing C), sometimes he will decide not to attack a viable user (thereby foregoing a net gain of G). Thus he faces a binary classification problem. Every attack results in either a true positive (viable user found) or false positive (non-viable user found). Ideal classification requires that the attacker know exactly which users will repay effort and which will not, and never makes the mistake of attacking unnecessarily or of leaving a viable target alone.

2.4 ROC curves

The trade-off between the two types of error is usually graphed as a Receiver Operator Characteristic (ROC) curve (*i.e.*, t_p *vs.* f_p) [22], an example of which is shown in Figure 1. The curve represents the ability to discriminate between viable and non-viable targets. Any point on the ROC curve represents a possible operating point or strategy for the attacker.

For example, one strategy is for the attacker to choose a threshold x^* and attack User(i) if $x_i > x^*$. The ROC curve is then generated by plotting the true and false positive rates achieved as we sweep x^* through all possible values. The actual shape of the ROC curve is determined solely by the distribution of x over viable and non-viable users. In fact, the ROC curve is the graph of $cdf(x \mid \text{viable})$ *vs.* $cdf(x \mid \text{non-viable})$.

Three easily-proved properties of ROC curves [22] will be useful in the following.

- The ROC curve is monotonically increasing: the true positive rate t_p is an increasing function of the false positive rate f_p.
- The ROC curve has monotonically decreasing slope: the slope dt_p/df_p is a decreasing function of f_p.
- The Area Under the Curve (AUC) is the probability that the classifier ranks a randomly chosen true positive higher than a randomly chosen false positive.

The first property, monotonicity, presents our attacker with his fundamental tradeoff. Since he is constrained to move on the ROC curve, the attacker can decrease false positives only by decreasing true positives and *vice versa*. Thus, his attack strategy must weigh the number of both types of error and their relative costs [22].

The AUC is often taken as a figure of merit for a classifier. The AUC for the ROC curve shown in Figure 1 is 0.9. This means that for a randomly chosen viable user i and a randomly chosen non-viable user j we will have $x_i > x_j$ 90% of the time. Clearly, the higher AUC the better the classifier.

2.5 Attack everyone, attack at random

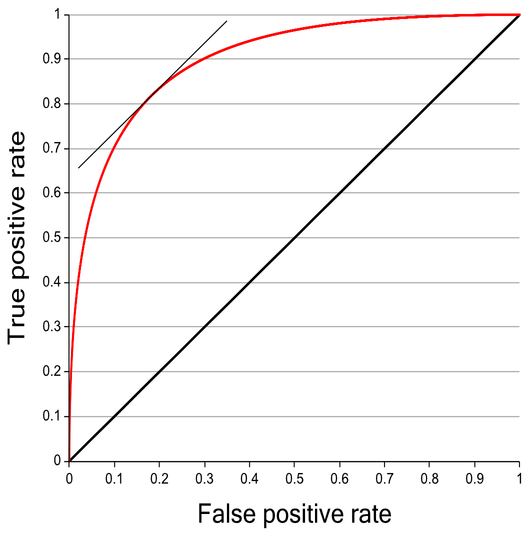


Figure 1: Example ROC curve showing the tradeoff between true and false positives. The point with unit slope tangent is profitable only if attacking everyone is profitable. Otherwise profitable strategies lie only to the left of that point.

The diagonal line in Figure 1 represents a random classifier, which makes decisions that are no better (and no worse) than random. That is, targets are attacked with uniform probability $1/N$. Any curve above this line is a better-than-random classifier: for a given false positive rate it achieves more true positives than the random classifier.

When attacking everyone $t_p = 1$ and $f_p = 1$. That is all viable and non-viable targets are attacked. When this happens the expected return is: $E\{R\} = (d \cdot G - (1-d) \cdot C) \cdot N$. Imposing the constraint that the expected return should be positive, $E\{R\} > 0$, gives:

$$d = \frac{M}{N} > \frac{C}{G+C}. \quad (2)$$

If this holds, then attacking everyone is a profitable proposition.

When $C > 0$ there is an intuitive explanation for this constraint. Attacking everyone is profitable so long as the density of viable targets is greater than the ratio of the costs of unsuccessful and successful attacks. For example, if 1% of users are viable targets then the net gain from a successful attack would have to be 99× the cost of an attack to make targeting the whole population profitable.

Attacking at random (*i.e.*, ignoring the score x_i) has the same expected return as attacking everyone.

In the special case where $C = 0$ (*i.e.*, it costs nothing to attack) making a profit is easy so long as there are some viable victims. Profit is guaranteed so long as true positives give some gain. Spam seems to be an example where $C \approx 0$. If false positives cost nothing, while false negatives mean lost income, there's little point in restraint. Equally, if $G \to \infty$ this strategy makes sense: if an attacker has infinite resources and places infinite value on each viable target he will attack everyone. In this paper we will assume that $C > 0$ and G is finite.

2.6 Optimal Operating Point

Since the slope of the ROC curve is decreasing the best ratio of true to false positives is in the lower left corner. In this region true positives are increasing rapidly, while false positives are increasing slowly. Going further right on the ROC involves adding false positives at an increasing rate. Operating in the lower left corner essentially involves attacking only targets that are almost "sure things." The problem with this strategy is that by going after only "sure things" it leaves most of the viable targets un-attacked.

For a single attacker the return is given by (1). This is maximized when $dE\{R\}/df_p = 0$, which gives:

$$\frac{dt_p}{df_p} = \frac{1-d}{d} \cdot \frac{C}{G}. \tag{3}$$

Thus, to maximize return, the attacker should operate at the point on the ROC curve with this slope. We refer to this point as the Optimal Operating Point (OOP). The point can be found by drawing a tangent with this slope to the ROC curve. Note that the slope at the OOP is determined by the density of viable targets in the population, and the ratio of net gain to cost.

Operating at this point does not mean that no viable victims will be found at operating points further to the right. However, if he moves to the right of the OOP, our attacker finds that the cost of false positives that are added now more than consumes the gain from true positives that are added. Optimality requires that many viable targets to the right are ignored. For maximum profit, the attacker does not attempt to find all viable targets, he tries to find the most easily found ones. Pursuing the least-likely viable targets (*i.e.*, those with smallest x values) makes no sense if they cannot be easily distinguished from false positives.

Operating to the right of the OOP makes no sense, however there are several good reasons why an attacker might operate to the left. To meet a finite budget, or reduce the variance of return an attacker might operate far to the left of the OOP. We explore these reasons in Section 3.6. Thus the return achieved at the OOP can be considered an upper bound (and sometimes a very loose one) on what can be achieved.

3. ROC CURVES AND THE PURSUIT OF PROFIT

Quantity	Symbol
Number of users	N
Number of viable users	M
Victim density	$d = M/N$
Net gain from viable user	G
Cost of attack	C
True positive rate	t_p
False positive rate	f_p
Number viable users attacked	$d \cdot t_p \cdot N$
Number non-viable users attacked	$(1-d) \cdot f_p \cdot N$

Table 1: Summary of notation and symbols used in this paper.

Having reviewed the basics of ROC curves we now explore some implications for our attacker. The best that an attacker can do is to operate at the point with slope given in (3). We assume that our attacker finds this point, either by analysis or (more likely) trial and error. We now explore the implications of the trade-off between true and false positives for the attacker's return.

3.1 As slope increases fewer users are attacked

We now show that as the slope at the OOP increases fewer users are attacked. Recall, from Section 2.4, that the ROC curve is monotonically increasing, but that its slope is monotonically decreasing with f_p. It follows that increasing slope implies decreasing f_p which in turn implies decreasing t_p. Thus, the higher the slope at the OOP, the lower both the true and false positive rates t_p and f_p.

This is significant because as our attacker decreases t_p and f_p he attacks fewer viable users (*i.e.*, $d \cdot t_p \cdot N$ is decreasing) and fewer total users (*i.e.*, $d \cdot t_p \cdot N + (1-d) \cdot f_p \cdot N$ is decreasing). Thus, as slope increases *not only are fewer total targets attacked, but fewer viable targets are attacked.* Thus the global social good is increased as the attacker retreats leftwards along the ROC curve. This is true whether our goal is to reduce the total number of targets attacked or the total number of viable targets attacked.

Pictorially this can be seen in Figure 1. At the top-right of the ROC curve, everyone is attacked and all viable targets are found. Here $t_p = 1$ and $f_p = 1$. This appears to be the case of broadcast attacks such as spam. These attacks are bad, not merely because viable victims are found and exploited, but all users suffer the attacks. It can reasonably be argued for broadcast attacks that the harm to the non-viable population is many times greater than the value extracted from the viable population. At the other extreme, in the bottom-left of the ROC curve nobody is attacked and no viable targets are found (*i.e.*, $t_p = 0$ and $f_p = 0$). Clearly, pushing the attacker to the left on his ROC curve is

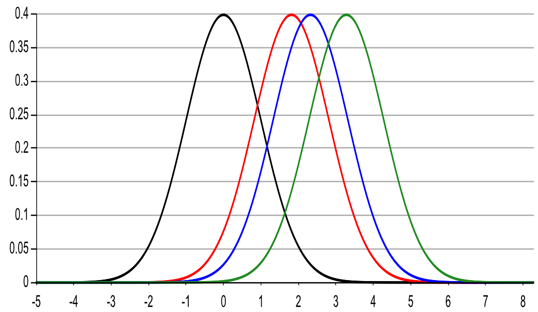


Figure 2: Distribution of x for normally distributed scores. The mean over non-viable users is zero (left-most curve). Various assumptions of the separation between viable and non-viable users are given. Means of $\mu = 1.18, 2.32$ and 3.28 result in the classifiers of Figure 3 which have 90%, 95% and 99% ability to tell randomly chosen viable users from non-viable.

very desirable.

3.2 If attacking everyone is not profitable slope must be greater than unity

We now show that the OOP must have slope > 1 unless attacking everyone is profitable. Suppose that the slope at the OOP is less than unity. From (3) this implies:

$$\frac{1-d}{d} \cdot \frac{C}{G} < 1.$$

Rearranging gives:

$$d > \frac{C}{G+C}$$

which is the same as (2), the condition to guarantee that attacking everyone is profitable. Thus, if attacking everyone is not profitable, then the slope at the OOP must be greater than unity.

Hence (when attacking everyone is not profitable) a line tangent to the ROC curve with unity slope establishes the point that is an upper bound on the true and false positive rates achievable with a given classifier. For example, in Figure 1 the tangent with unity slope intersects the ROC curve at $(f_p, t_p) \approx (0.182, 0.818)$. Thus 81.8% is an upper bound on the fraction of viable targets that will be attacked using the optimal strategy. Similarly, 18.2% is an upper bound on the fraction of non-viable targets that will be attacked.

Since we assume merely that attacking all users is not profitable both of these bounds are very loose. They are instructive nonetheless. The absolute best of circumstances, for this ROC curve, result in a little over 80% of viable targets being attacked. An attacker who does not face competition from other attackers, who

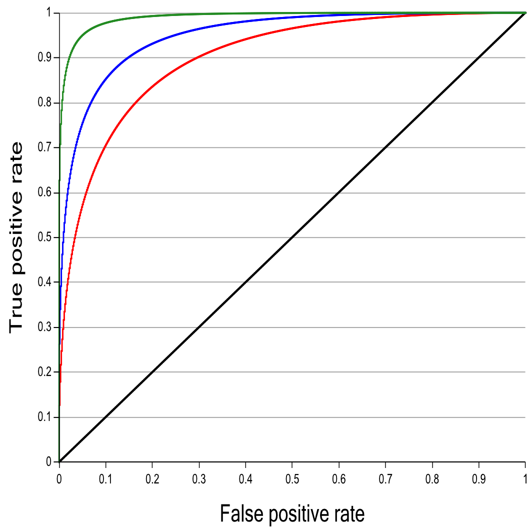


Figure 3: ROC curves for a single attacker with perfect knowledge. The observables are normally distributed for both viable and non-viable users with only the mean changing. The AUC (*i.e.*, probability that the attacker can tell a viable user from non-viable) are 90%, 95% and 99%.

has perfect information about the viability probabilities, and who knows precisely the density, d, of viable victims in the population will still attack no more than 81.8% of viable targets when maximizing his profit in this example. If we relax any of these assumptions then he maximizes his profit by attacking even fewer viable targets. We examine deviations from the ideal case in Section 3.6.

The argument at unity slope can be (approximately) repeated at other (higher) slopes. If attacking all of the top $1/W$ is profitable then attacking a population with density dW is profitable in which case (2) gives

$$d > \frac{C}{W \cdot (G+C)}.$$

From (3) if the slope at the OOP is less than W then

$$d > \frac{C}{W \cdot G + C}.$$

The second constraint is looser than the first, but only by a little if we assume that $G \gg C$ (*i.e.*, gain from successful attack is much greater than cost). Thus, if attacking the top $1/W$ of the population (sorted in descending order of viability estimate x_i) is not profitable then the slope at the OOP $\approx W$. For expensive attacks, the slope at the OOP will be very high. For example, where attacking all of the top 1% of the population is not profitable, the slope must be about 100. In the example ROC curve shown in Figure 1 this is achieved at $t_p = 0.0518$ and $f_p = 0.00029$; *i.e.*, only 5.18% of viable victims are attacked. If attacking all of the top 0.1% of the population is not profitable then we might expect a slope of about 1,000, which is achieved at $t_p = 0.0019$ so that only 0.19% of viable victims would be attacked. This pushes the attacker to the extreme left of the ROC curve, where (as we saw in Section 3.1) social good is increased and fewer users are attacked.

3.3 As density decreases slope increases

Observe that as the density of viable targets, d, decreases, the slope at the OOP (given in (3)) increases. Recall (from Section 2.6) that the slope of the ROC curve is monotonically decreasing. Thus, as $d \to 0$, the optimal operating point will retreat leftward along the ROC curve. As we've seen in Section 3.1 this means fewer true positives and fewer total users attacked. Hence, as the number of viable targets decreases the attacker must make more conservative attack decisions. This is true, even though the gain G, cost C and ability to distinguish viable from non-viable targets is unchanged.

For example, suppose, using the ROC curve of Figure 1, an attack has $G/C = 9$, *i.e.*, the gain from a successful attack is $9\times$ the cost of an unsuccessful one. Further suppose $d = 1/10$ which makes the slope at the OOP equal to one. We already saw that the unity slope tangent resulted in only 81.8% of viable targets and 18.2% of non-viable targets being attacked. Since $d = 1/10$ we have that 10% of users are viable targets. Thus, $0.818 \times 0.1 = 0.0818$ or 8.18% of the population are successfully attacked and $0.818 \times 0.1 + 0.182 \times 0.9 = 0.246$ or 24.6% of all users will be attacked.

Now suppose that the density is reduced by a factor of 10 so that $d = 1/100$. Everything else remains unchanged. From (3) the slope at the OOP must now be: $100 \times (1 - 1/100) \times 1/9 = 11$. Not shown, but the tangent with this slope intersects the ROC curve in Figure 1 at approximately $t_p = 0.34$ and $f_p = 0.013$. Thus, the optimal strategy now attacks only 34.0% of viable targets and 1.3% of non-viable targets. Since $d = 1/100$ we have that 1% of users are viable targets. Thus, $0.34 \times 0.01 = 0.0034$ or 0.34% of the population are successfully attacked and $0.34 \times 0.01 + 0.013 \times 0.99 = 0.0163$ or 1.63% of all users are attacked. Hence, in this case, a $10\times$ reduction in the victim density reduces the number of true positives by almost $24\times$ and the number of all attacked users by about $15\times$.

While the exact improvement depends on the particular ROC curve, dramatic deterioration in the attacker's situation is guaranteed when density gets low enough. Independent of the ROC curve, it is easy to see from (3) that a factor of K reduction in density implies at least a factor of K increase in slope (for $K > 1$). For many classifiers the slope of the ROC tends to ∞ as $f_p \to 0$. (We show some such distributions in Section 3.4.) Very high slope for small values of density implies that the true positive rate falls very quickly with further decreases in d.

3.4 Different ROC Curves

We have used the ROC curve of Figure 1 to illustrate several of the points made. While, as shown in Section 3.3, it is always true that decreasing density reduces the optimal number of viable victims attacked the numbers given were particular to the ROC curve, gain ratio G/C and density d chosen. We now examine some alternatives.

As stated earlier, a convenient parametric model is to assume that $pdf(x \mid \text{viable})$ and $pdf(x \mid \text{non-viable})$ are drawn from the same distribution with different means. For example, with unit-variance normal distribution we would have $pdf(x \mid \text{non-viable}) = \mathcal{N}(0,1)$ and $pdf(x \mid \text{viable}) = \mathcal{N}(\mu,1)$. That is, by choosing μ we can achieve any desired degree of overlap between the two populations. This is shown in Figure 2 for three different values of μ. When μ is small the overlap between $\mathcal{N}(0,1)$ and $\mathcal{N}(\mu,1)$ is large and the classifier cannot be very good. As μ increases the overlap decreases and the classifier gets better.

The ROC curves for the distributions shown in Figure 2 are given in Figure 3 with values of AUC$= 0.9, 0.95$ and 0.99. The rightmost curve in Figure 2 corresponds to the uppermost (*i.e.*, best) classifier in Figure 3. These correspond to an attacker ability to distinguish randomly chosen viable from non-viable 90%, 95% and 99% of the time. The highest curve (*i.e.*, AUC $= 0.99$) is clearly the best among the classifiers.

This parametric model, using normal distributions is very common in detection and classification work [22]. It has an additional advantage in our case. Viability often requires the AND of many things; for example it might require that the victim have money, and have a particular software vulnerability, and do banking on the affected machine and that money can be moved irreversibly from his account. The lognormal distribution is often used to model variables that are the product of several positive variables, and thus is an ideal choice for modeling the viability variable x. Since the ROC curve is unaffected by a monotonic transformation of x the curves for $pdf(x \mid \text{non-viable}) = \ln \mathcal{N}(0,1)$ and $pdf(x \mid \text{viable}) = \ln \mathcal{N}(\mu,1)$ are identical to those plotted in Figure 3.

In Figure 4 we plot the slope of each of these ROC curves as a function of $\log_{10} t_p$. These show that large slopes are achieved only at very small true positive rates. For example, a slope of 100 is achieved at a true positive rate of 5.18%, 20.6% and 59.4% by the curves with AUC of $0.9, 0.95$ and 0.99 respectively. Similarly, a slope of 1000 is achieved at 0.19%, 3.52% and 32.1% re-

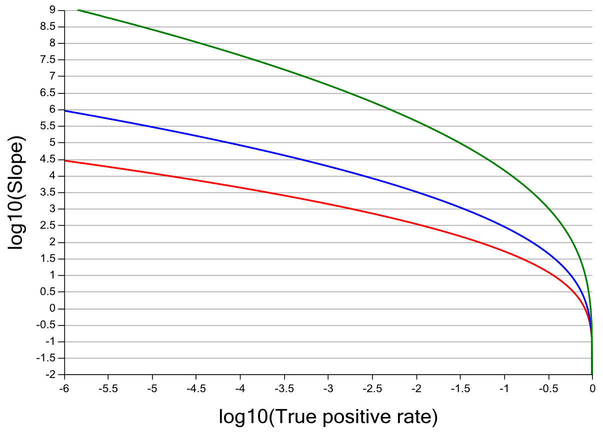


Figure 4: Slope versus true positive rate, t_p, for the curves shown in Figure 3. Observe that when the slope must be high, the true positive rate falls rapidly. Even for the best classifier (upper curve) a slope of 1000 is achieved at $t_p = 0.321 \approx \log_{10}(-0.494)$.

spectively. Thus, for example, if the density d and gain ratio G/C indicated that the OOP should have slope 1000 then an attacker using the AUC= 0.95 classifier would optimally attack only 3.52% of viable users.

If we fix G/C we can plot the true positive rate, t_p, as a function of victim density, d. This has been done in Figure 5 (a) using a value of $G/C = 20$ and (b) using a value of $G/C = 100$. For example, from Figure 5 (a), using the AUC= 0.95 classifier the true positive rate will be 0.683, 0.301, 0.065 and 0.0061 when victims represent 1%, 0.1%, 0.01% and 0.001% of the population respectively. To emphasize: low victim densities results in smaller and smaller fractions of the viable victims being attacked.

Finally, in Figure 6 (a) and (b) we plot the fraction of the population successfully attacked (*i.e.*, $d \cdot t_p$ *vs.* d) again using values of $G/C = 20$ and 100. Observe that the fraction of the population attacked always falls faster (and generally much faster) than d. For example, when $G/C = 100$ and AUC=0.9 a factor of 10 reduction of d from 10^{-5} to 10^{-6} causes about a factor of 1000 reduction in the fraction of the population successfully attacked.

3.5 Diversity is more important than strength

The dramatic fall of the fraction victimized with d shown in Figure 6 suggests that many small attack opportunities are harder to profitably exploit than one big one. We now show that this is indeed the case. From the attacker's point of view the sum of the parts is a lot smaller than the whole.

Recall, for an attack campaign, that the number of victims found is $d \cdot t_p \cdot N$. Suppose we have two target populations each with viable victim densities $d/2$. Let's compare the two opportunities with densities $d/2$ with a single opportunity with density d. Assume that the distribution of scores x doesn't change. Thus, all three will have the same shaped ROC curve (since the ROC curve depends only on the distribution of the x_i), though different OOP's will be appropriate in exploiting them (since the OOP depends on d). For clarity, in the remainder of this section we will label t_p and f_p as being explicit functions of density; *e.g.*, $t_p(d/2)$ is the true positive rate for the opportunity with density $d/2$ *etc.*

Since t_p is monotonically decreasing with slope, and slope at the OOP is monotonically increasing as d decreases we have $t_p(d/2) < t_p(d)$. Thus,

$$d/2 \cdot t_p(d/2) \cdot N + d/2 \cdot t_p(d/2) \cdot N < d \cdot t_p(d) \cdot N.$$

The left-hand side is the number of viable victims attacked in the two opportunities and the right-hand side is the number attacked in the single joint opportunity. Thus, the attacker gets fewer victims when attacking two small populations than when attacking a larger population.

For example, consider the ROC curve shown in Figure 1. Suppose there are $d \cdot N = (d/2 + d/2) \cdot N$ targets in the overall population. Suppose the optimal operating point (given by (3)) dictates a slope of 11 when attacking the opportunity with density d. We already saw that this corresponds to a value of $t_p(d) = 0.340$ in Figure 1. Thus, $d \cdot 0.340 \times N$ users become victims. Now, if we split the viable victims into two populations of density $d/2$ the slope at the OOP must be > 22. This occurs at $t_p(d/2) = 0.213$ in Figure 1. Thus, $d/2 \cdot 0.213 \cdot N + d/2 \cdot 0.213 \cdot N = d \cdot 0.213 \cdot N$ users become victims; *i.e.*, the true positive rate (the fraction of viable users attacked) has fallen from 34% to 21.3%.

This benefit of diversity becomes even more obvious as we continue to split the target pool into small groups. Suppose the targets are divided into 20 categories, each representing a viable density of $d/20$. The OOP must now have slope $> 20 \times 11 = 220$. The point with slope 220 in Figure 1 occurs at $t_p = 0.01962$. Thus, over these 20 opportunities 1.96% of users become victims, a factor of 17× lower than if they were part of the same vulnerability pool. Thus, when presented with 20 smaller vulnerable populations the attacker successfully attacks a factor of 17× fewer users. Diversity in the attacks that succeed hugely improves the outcome for the user population, even when there is no change in the number of vulnerable users or the cost and gain associated with attacks.

3.5.1 *Everybody vulnerable, almost nobody attacked*

The number of viable users attacked for a single attack of density d is $d \cdot t_p(d) \cdot N$. If we divide into Q different opportunities of size d/Q the number of viable victims attacked is:

$$\frac{d}{Q} \cdot \sum_{k=1}^{Q} t_p(d/Q) \cdot N = d \cdot t_p(d/Q) \cdot N.$$

Since $t_p(d/Q) \ll t_p(d)$ for large Q the fragmented opportunity is always worse for the attacker than the single large opportunity.

In fact, as shown in Figure 4, $t_p(d/Q)$ can be made arbitrarily small for large Q. Thus it is trivially easy to construct scenarios where 100% of the population is viable, but where the most profitable strategy will involve attacking an arbitrarily small fraction. For example, if we choose $d = 1$ (everyone viable) and Q large enough so that $t_p(d/Q) < 0.01$ then all users are viable, but the optimal strategy attacks fewer than 1% of them. Consulting Figure 5 (a), for example, we see that for the AUC$=0.9$ classifier the true positive rate at $d = 10^{-4}$ is < 0.01. Thus, if we have 10,000 distinct attack types, each of which has a density of 1-in-10,000 then the entire population is vulnerable and viable, and yet the optimal strategy for the attacker results in fewer than 1% of users being victimized.

This helps formalize the observation that diversity is important in avoiding attacks [11] and explains why attacks appropriate to small victim densities are of little concern to the whole population.

3.6 Deviations from the Ideal

3.6.1 Budget-constrained attacker

We chose $G/C = 20$ and $G/C = 100$ in Figure 5 to illustrate the decay of profitability with density: as the density of viable victims decreases the fraction of that decreasing population that can be successfully identified shrinks. Even with good classifiers it appears that attacks with very small victim densities are hard to attack profitably. For example, when $G/C = 100$ and AUC$=0.9$ if 1-in-100,000 users are viable, then $t_p = 0.04$. That is, a population of 200 million users will contain 2000 viable users, of which 80 will be attacked using the optimal strategy. Fully, 96% of the viable users (who succumb if attacked and yield a $100\times$ payback for the investment) will escape harm because there is no strategy to attack them without also attacking so many non-viable users as to destroy the profit.

The example numbers we have chosen $G/C = 20$ and $G/C = 100$ might appear small. That is, might it not be possible that the gain, G, is not 20 or 100 times the cost of an attack, but 1000 or 10,000 or a million? Low success rates happen only when the slope at the OOP is high. Very high values of G/C would have (3) imply modest values of slope at the OOP even at small densities. We argue now against this view. In fact, if G/C is very large the attacker may have to be even more conservative.

The rate of change of t_p with respect to f_p at the OOP is given by (3). At this point the attacker finds one viable user for every

$$\frac{d}{1-d} \cdot \frac{dt_p}{df_p} = \frac{G}{C}$$

false positives. Effectively, his return resembles a $G/C+1$ sided coin. He gains G when the desired side comes up, but otherwise loses C. The strategy is optimal and profitable on the average: if he plays long enough he wins the maximum possible amount. However, the variance of the return is very high when the number of attacks on the order of $O(G/C)$. For example, suppose $G/C = 1000$ and $d = 10^{-4}$. The probability of not finding a single victim after 1000 attacks is $\text{binocdf}(0, 1000, 0.001) = 36.8\%$. If this happens the attacker is severely in the red. To be concrete, if $C = \$20$ he is down \$20,000, and even a successful attack won't put him back in the black. The fact that operating at the OOP is the most profitable strategy is of little consolation if he has a fixed budget and doesn't find a victim before it is exhausted. For example, at \$20 per attack, an attacker who starts with a fixed budget of \$10,000 would find it exhausted with probability $\text{binocdf}(0, 500, 0.001) = 60.1\%$ before he found his first victim. Echoing Keynes we might say that the victims can stay hidden longer than our attacker can stay solvent.

Thus, a budget-constrained attacker, at least in the beginning, must be very conservative. If he needs a victim every 20 attacks then he must operate at a point with slope

$$\frac{1-d}{d} \cdot \frac{1}{20} \text{ rather than } \frac{1-d}{d} \cdot \frac{C}{G}.$$

Hence, even if G/C is very large, he cannot afford the risk of a long dry patch before finding a profitable victim. This hugely influences the conservatism of his strategy. For example, if $d = 10^{-4}$ and $G/C = 1000$, the optimal strategy would have the attacker operate at the point on the ROC with slope ≈ 10 but if ne needs a victim every 20 attacks he would operate at a point with slope 500. Figure 4 shows the dramatic effect this has on the true positive rate.

Similarly, when G/C is large the variance of the return is very high at the OOP. The attacker finds one victim on average in every $G/C+1$ attempts. The mean number of victims found after k attacks is $k \cdot C/G$, but the variance is $(1 - C/G) \cdot k \cdot C/G$. Thus, returns will vary wildly. As before, if he has resources and can play long enough, it evens out. However, to persevere in a strategy that has a 36.8% chance of delivering zero victims after $k = G/C = 1000$ attacks requires confidence that our attacker has not mis-estimated the parameters.

In Section 3.6.2 we show that optimistic assessments of victim density, classifier accuracy or gain ratio can reduce the return by orders of magnitude. However, the attacker has no real way of estimating any of these parameters except by trial and error. Thus an attacker who goes 500 attacks without a victim has no good way of determining whether this the expected consequences of operating at the OOP when G/C is high (and profitable victims will come with persistence) or whether he has entirely overestimated the opportunity (and his attack strategy will bankrupt him if he perseveres). While victim density, classifier accuracy and gain ratio might remain relatively stable over time if a single attacker has the opportunity to himself, this might not be the case if other attackers begin to target the same viable victim pool. For all of these reasons we argue that, even when G/C is high, the attacker will not operate at the OOP with slope given by (3) but at a far more conservative point with slope:

$$\frac{1-d}{d} \cdot \frac{1}{k_{max}}, \tag{4}$$

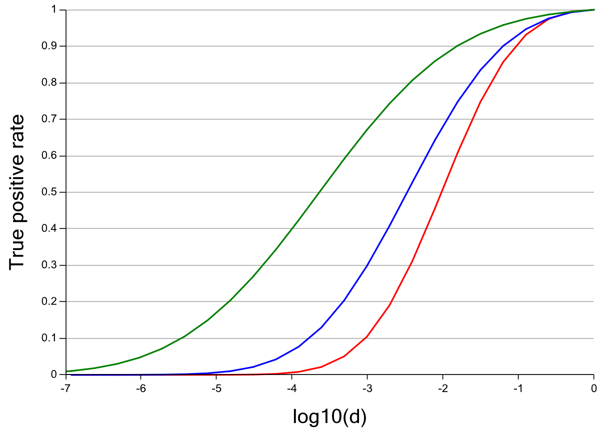
where k_{max} is the maximum average number of attacks he is willing to go between successes. This value, k_{max}, is determined by his fear of exhausting his budget, having too high a variance and having density decrease due to factors such as other attackers joining the pool.

3.6.2 Optimism does not pay

The analysis for optimum profit assumes several things. It assumes that the attacker knows the density of viable victims d, the gain ratio G/C and correctly chooses the optimal strategy for thresholding the viability scores x. It assumes that he does not compete for viable victims with other attackers.

All of these assumptions seem generous to the attacker. Widely circulated estimates of how many victims fall to various attacks, and the amounts that are earned by attackers turn out to be little better than speculation [8]. Thus, it would appear that the attacker can learn d and G/C only by trial and error. Further, in the process of estimating what value of x best separates viable from non-viable users he most likely has only his own data to use. Classifiers in science, engineering, medicine and other areas are often optimized using data from many who are interested in the same problem. Pooling improves everyone's performance. However, in crime competition only reduces return, so the successful and unsuccessful trials of other attackers is unlikely to be available to him.

Figure 5 shows the catastrophic effect that optimism can have. An attacker who assumes that d is larger than it is suffers in two ways. First, there are simply fewer viable victims: the opportunity is smaller than he imagines. Second the true positive rate using the optimal strategy drops rapidly with density: he ends



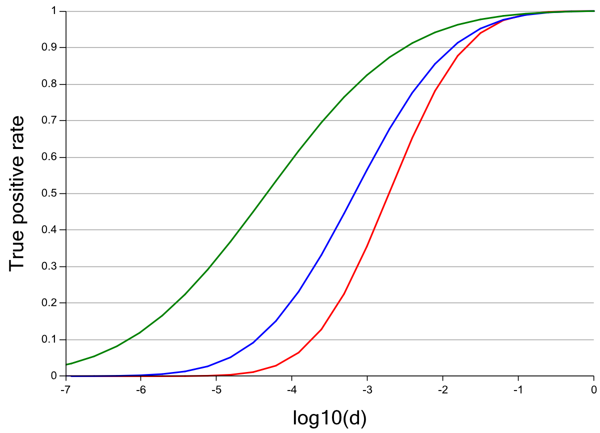


Figure 5: True positive rate for classifiers shown in Figure 3. These curves assumed gain ratio (a) $G/C = 20$, and (b) $G/C = 100$. Observe that as viable user density decreases the fraction of viable users attacked plummets. For example, when $G/C = 20$ and viable users are 1-in-100,000 of the population (*i.e.*, $\log_{10} d = -5$) the best classifier attacks only 32% of viable users, while the other classifiers attack 4% and 1% respectively.

up getting a smaller fraction of a smaller pool than he thought.

For example, consider an attacker who over-estimates his abilities. He believes he can distinguish viable from non-viable 99% of the time when he can really do so only 90% of the time, that G/C will average to be 100 when it actually averages 20, and that the density of viable victims is 1-in-1000 when it is actually 1-in-10,000. Thus, he expects $t_p = 0.826$ (*i.e.*, the value of t_p at $\log_{10} d = -3$ in the upper curve of Figure 5 (b)) but gets only $t_p = 0.006$ (*i.e.*, the value of t_p at $\log_{10} d = -4$ in the lower curve of Figure 5 (a)). The factor difference between what he expected and achieves is:

$$\frac{d \cdot t_p \cdot G/C}{d' \cdot t'_p \cdot G'/C'} = \frac{10^{-3} \cdot 0.826 \cdot 100}{10^{-4} \cdot 0.006 \cdot 20} = 6,883.$$

That is, a factor of 10 overestimate of density, a factor of 5 overestimate of gain and believing his ability to distinguish viable from non-viable to be 99% rather than 90% results in almost four orders of magnitude difference in the outcome. Optimistic assessments of ability or opportunity are punished severely.

3.7 Opportunities with low victim densities

Figures 5 and 6 illustrate the challenging environment an attacker faces when victim density is low. When $d = 10^{-5}$ or 10^{-6} even the best of the classifiers examined will leave the majority of viable victims un-attacked. These curves were calculated for the cases of $G/C = 20$ and 100. We argued in Section 3.6.1 that it is risky or infeasible in most cases to assume higher values of G/C. Even if G/C is very large it is safer to operate at the point with slope given by (4) rather than the OOP.

The sole remaining avenue to improve the low success rates suggested by Figures 5 and 6 is the quality of the classifier. We have used the classifiers shown in Figure 3 which have 90%, 95% and 99% ability to distinguish viable from non-viable. Might it not be possible that our attacker can actually discriminate between randomly selected users from the two classes not 99% of the time, but 99.999% of the time, or even higher? This would certainly alter his situation for the better: the true positive rate of a classifier with AUC=0.99999 might be very respectable even at $d = 10^{-6}$ and $G/C = 100$.

However, this appears very unlikely. Building classifiers generally requires data. There is no difficulty, of course, in finding examples of non-viable users, but when d is low examples of viable users are, by definition, extremely rare. But many examples of both viable and non-viable users are required to get any accuracy. If it can be achieved at all, a classifier with AUC=0.99 might require hundreds of examples of viable victims for training. Thus, our attacker faces a Catch-22. At low victim densities an extremely good classifier is required for profitability; but training a good classifier requires

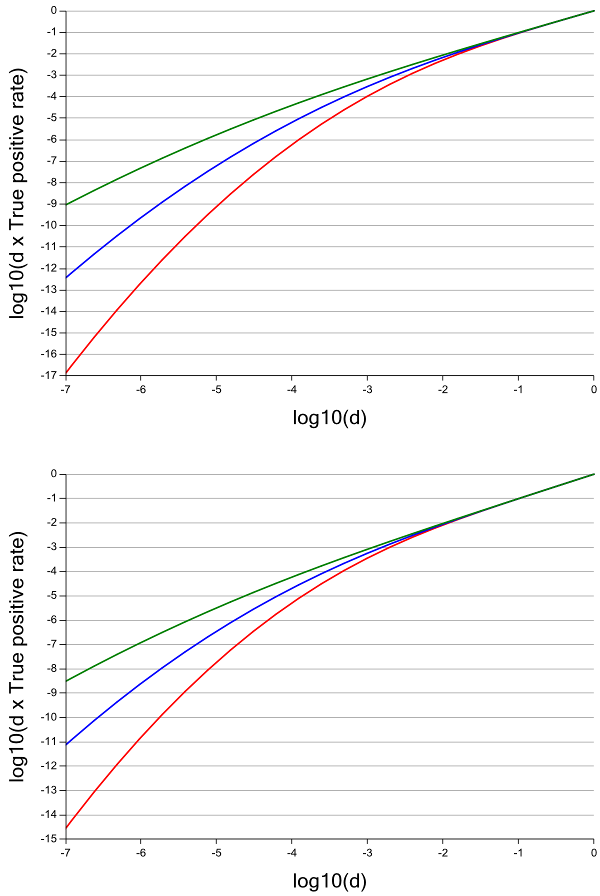


Figure 6: Fraction of population successfully attacked (*i.e.*, $d \cdot t_p$) *vs.* victim density, d, for classifiers shown in Figure 3. These curves used a gain ratio of (a) $G/C = 20$, and (b) $G/C = 100$. Observe that the fraction of users successfully attacked always falls faster than density, and generally far faster than density. For example, when $G/C = 100$ and AUC=0.9 a factor of 10 reduction of d from 10^{-5} to 10^{-6} causes a factor of 1000 reduction in the fraction of the population successfully attacked.

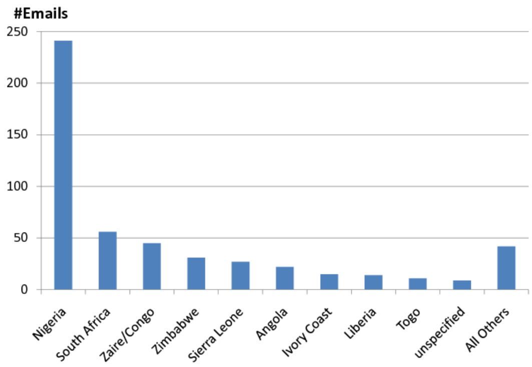


Figure 7: Country of claimed origin for 419 emails.

examples of many viable users, which are hard to find.

Ironically, for the attacker, more accurate classifiers are much more easily built where they are least needed: where victim densities are high. Figures 6 (b) shows that even the worst classifier succeeds almost 1% of the time when $d = 10^{-2}$. The viable users found can then be used to train and make the classifier even better. However, when $d = 10^{-5}$ this same classifier succeeds only over a portion 10^{-8} of the population; *i.e.*, it can profitably find only a handful of victims in a population of 200 million.

Thus, while it is plausible that an attacker might have 99.999% ability to distinguish viable users from non-viable at high victim densities, it is almost impossible to believe that this might be the case when d is low. It's hard to build algorithms that are very accurate at detecting rare things, because rare things are, well, rare. Faith that very accurate classifiers for very rare events can be built without training data is generally confined to those who are deluded, or have the luxury of never putting their claims to the test.

4. DISCUSSION

4.1 Why do Nigerian scammers say that they are from Nigeria?

An examination of a web-site that catalogs scam emails shows that 51% mention Nigeria as the source of funds [1], with a further 34% mentioning Côte d'Ivoire, Burkina Faso, Ghana, Senegal or some other West African country (see Figure 7). This finding is certainly supported by an analysis of the mail of this genre received by the author.

Why so little imagination? Why don't Nigerian scammers claim to be from Turkey, or Portugal or Switzerland or New Jersey? Stupidity is an unsatisfactory answer: the scam requires skill in manipulation, considerable inventiveness and mastery of a language that is non-native for a majority of Nigerians. It would seem odd that after lying about his gender, stolen millions, corrupt officials, wicked in-laws, near-death escapes and secret safety deposit boxes that it would fail to occur to the scammer to lie also about his location. That the collection point for the money is constrained to be in Nigeria doesn't seem a plausible reason either. If the scam goes well, and the user is willing to send money, a collection point outside of Nigeria is surely not a problem if the amount is large enough.

"Nigerian Scam" is one of five suggested auto-completes in a Google search for "Nigeria" (see Figure 8 retrieved May 8, 2011). Thus, if the goal is to maximize response to the email campaign it would seem that mentioning "Nigeria" (a country that to many has become synonymous with scams) is counter-productive. One could hardly choose a worse place to claim to be from if the goal is to lure the unwary into email communication.

The scam involves an initial email campaign which has almost zero cost per recipient. Only when potential victims respond does the labor-intensive and costly effort of following up by email (and sometimes phone) begin. In this view everyone who enters into email communication with the scammer is "attacked" (*i.e.*, engenders a cost greater than zero). Of these, those who go the whole distance and eventually send money are true positives, while those who realize that it is a scam and back out at some point are false positives.

If we assume that the scammer enters into email conversation (*i.e.*, attacks) almost everyone who responds his main opportunity to separate viable from non-viable users is the wording of the original email. If the goal is to attack as many people as possible, then the email should be designed to lure as many as possible. However, we've seen that attacking the maximum number of people does not maximize profit. Operating at the OOP involves attacking only the most likely targets. Who are the most likely targets for a Nigerian scammer? Since the scam is entirely one of manipulation he would like to attack (*i.e.*, enter into correspondence with) only those who are most gullible. They also need, of course, to have money and an absence of any factors that would prevent them from following through all the way to sending money.

Since gullibility is unobservable, the best strategy is to get those who possess this quality to self-identify. An email with tales of fabulous amounts of money and West African corruption will strike all but the most gullible as bizarre. It will be recognized and ignored by anyone who has been using the Internet long enough to have seen it several times. It will be figured out by anyone savvy enough to use a search engine and follow up on the auto-complete suggestions such as shown in Figure 8. It won't be pursued by anyone who consults sensible family or fiends, or who reads any of the advice banks and money transfer agencies make available. Those who remain are the scammers ideal targets. They represent a tiny subset of the overall population. In the language of our analysis the density of viable victims, d, is very low: perhaps 1-in-10,000 or 1-in-100,00 or fewer will fall for this scam.

As we've seen, in Section 3.3, at low victim densities the attack/don't attack decisions must be extremely conservative. If only 0.00001% of the population is viable then mistakenly attacking even a small portion of the 99.999% of the population that is non-viable destroys profit. The initial email is effectively the attacker's classifier: it determines who responds, and thus who the scammer attacks (*i.e.*, enters into email conversation with). The goal of the email is not so much to attract viable users as to repel the non-viable ones, who greatly outnumber them. Failure to repel all but a tiny fraction of non-viable users will make the scheme unprofitable. The mirth which the fabulous tales of Nigerian scam emails provoke suggests that it is mostly successful in this regard. A less outlandish wording that did not mention Nigeria would almost certainly gather more total responses and more viable responses, but would yield lower overall profit. Recall, that viability requires that the scammer actually extract money from the victim: those who are fooled for a while, but then figure it out, or who balk at the last hurdle are precisely the expensive false positives that the scammer must deter.

In choosing a wording to dissuade all but the likeliest prospects the scammer reveals a great sensitivity to false positives. This indicates that he is operating in the far left portion of the ROC curve. This in turn suggests a more precarious financial proposition than is often assumed.

4.2 Putting false positives to work

We find that, when $C > 0$, the attacker faces a problem familiar to the rest of us: the need to manage the ratio of false to true positives drives our decisions. When this is hard he retreats to the lower left corner of the ROC curve. In so doing he attacks fewer and fewer viable targets. This is good news.

We now explore how we can make this even better and exploit this analysis to make an attacker's life even harder. Great effort in security has been devoted to reducing true positives. User education, firewalls, antivirus products *etc*, fall into this camp of trying to reduce the likelihood of success. There has also been effort on reducing G the gain that an attacker makes. These are techniques that try to reduce the value of the stolen goods; fraud detection at the back-end might be an instance of reducing the value of stolen passwords or credit cards. There has been some effort at increasing

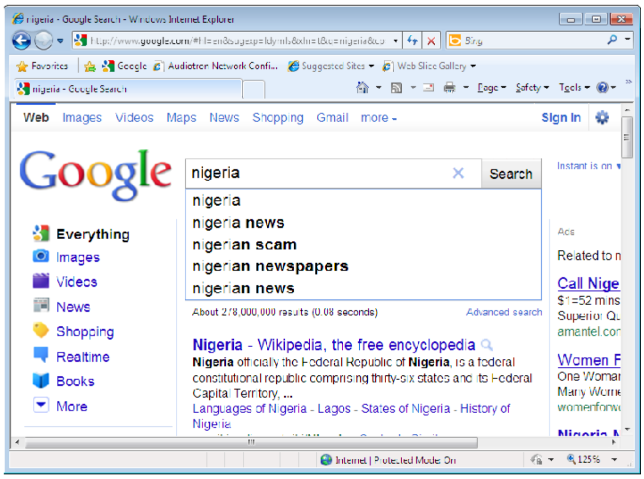


Figure 8: Google search offering "Nigerian Scam" as an auto-complete suggestions for the string "Nigeria".

C. Proposals to add a cost to spam, and CAPTHCHA's fall into this camp [6, 4]. Relatively unexplored is the option of intentionally increasing f_p with the goal of wasting attacker resources. If we inject false positives (*i.e.*, non-viable but plausible targets) we reduce the viable target density. As we saw in Section 3.3 this causes a deterioration in the attackers prospects and improves the social good. If we can increase f_p to the point where the expected return in (1) becomes negative the attack may be uneconomic.

It is, of course, entirely obvious that adding false positives reduces the attacker's return. Scam-baiters, for example, who intentionally lure Nigerian scammers into time-wasting conversations have this as one of their goals [2]. What is not obvious, and what our analysis reveals, is how dramatic an effect this can have. We saw in Section 3.4 that a 10× reduction in density could produce a 1000× reduction in victims found.

Inserting false positives effectively reduces the viable victim density. Figure 6 reveals that the portion of the population successfully attacked falls much faster than victim density, and that this trend accelerates as d decreases. For example, in Figure 6 (a) for the AUC= 0.9 classifier the 10× reduction in d from 10^{-2} to 10^{-3} produces a 45× reduction in $d \cdot t_p$, while the reduction in d from 10^{-5} to 10^{-6} produces a 3500× reduction. This reiterates that at low densities the attacker is far more sensitive to false positives.

5. RELATED WORK

The question of tradeoffs in security is not a new one. Numerous authors have pointed out that, even though security is often looked at as binary, it cannot escape the budgeting, tradeoffs and compromises that are inevitable in the real world. The scalable nature of many web attacks has been noted by many authors, and indeed this has often been invoked as a possible source of weakness for attackers. Anderson [18] shows that incentives greatly influence security outcomes and demonstrates some of the perverse outcomes when they are mis-aligned. Since 2000 the Workshop on the Economics of Information Security (WEIS) has focussed on incentives and economic tradeoffs in security.

Varian suggests that many systems are structured so that overall security depends on the weakest-link [13]. Gordon and Loeb [16] describe a deferred investment approach to security. They suggest that, owing to the defender's uncertainty over which attacks are most cost effective, it makes sense to "wait and see" before committing to investment decisions. Boehme and Moore [20] develop this approach and examine an adaptive model of security investment, where a defender invests most in the attack with the least expected cost. Interestingly, in an iterative framework, where there are multiple rounds, they find that security under-investment can be rational until threats are realized. Unlike much of the weakest-link work, our analysis focusses on the attacker's difficulty in selecting profitable targets rather than the defender's difficulty in making investments. However, strategies that suggest that under-investment is not punished as severely as one might think spring also from our findings.

Grossklags *et al.*[12] examine security from a game theoretic framework. They examine weakest-link, best-shot and sum-of-effort games and examine Nash equilibria and social optima for different classes of attacks and defense. They also introduce a weakest-target game 'where the attacker will always be able to compromise the entity (or entities) with the lowest protection level, but will leave other entities unharmed." A main point of contrast between our model and the weakest-target game is that in our model those with the lowest protection level get a free-ride. So long as there are not enough of the to make the overall attack profitable, then even the weakest targets escape.

Fultz and Grossklags [17] extend this work by now making the attacker a strategic economic actor, and extending to multiple attackers. As with Grossklags *et al.*[12] and Schechter and Smith [21] attacker cost is not included in the model, and the attacker is limited mostly by a probability of being caught. Our model, by contrast, assumes that for Internet attackers the risk of apprehension is negligible, while the costs are the main limitation on attacks.

In earlier work we offered a partial explanation for why many attacks fail to materialize [14]. If the attack opportunities are divided between targeted attackers (who expend per-user effort) and scalable attackers (who don't) a huge fraction of attacks fail to be profitable since targeting is expensive. This paper extends this work and shows that even scalable attacks can fail to be economic. A key finding is that attacking a crowd of users rather than individuals involves facing a sum-of-effort rather than weakest-link defense. The greater robustness and well-known free-rider effects that accompany sum-of-effort systems form most of the explanation for the missing attacks. Florêncio and Herley [9] address the question of why many attacks achieve much less harm than they seem capable of. Their model suggests that an attacker who is constrained to make a profit *in expectation* will ignore many viable targets.

Odlyzko [3] addresses the question of achieving security with insecure systems, and also confront the paradox that "there simply have not been any big cybersecurity disasters, in spite of all the dire warnings." His observation that attacks thrive in cyberspace because they are "less expensive, much more widespread, and faster" is similar to our segmentation of broadcast attacks.

While trade-off problems have been extensively studied not much work has examined the problem from an attacker point of view. Dwork and Naor [6] examine the question of increasing the cost of all attacks. They note the danger of situations where costs are zero and suggest various ways that all positives (not just false ones) can be increased in cost. Their insight is that when false positives outnumber legitimate use then a small cost greatly interferes with attacks for minimal effect on legitimate use. Schechter and Smith [21] investigate various investment strategies to deter attackers who face the risk of penalties when attacks fail. Ford and Gordon [10] suggest enlisting many virtual machines in botnets. These machines join the network, but refuse to perform the valuable business functions (*e.g.*, sending spam) and thus make the value of the botnet less predictable. Scambaiters [2] advocate wasting attacker time. However this is done manually, rather than in an automated way, and for sport rather than to reduce their profitability.

6. CONCLUSION

We explore attack decisions as binary classification problems. This surfaces the fundamental tradeoff that an attacker must make. To maximize profit an attacker will not pursue all viable users, but must balance the gain from true positives against the cost of false positives. We show how this difficulty allows many viable victims to escape harm. This difficulty increases dramatically as the density of viable victims in the population decreases. For attacks with very low victim densities the situation is extremely challenging. Unless viable and non-viable users can be distinguished with great accuracy the vast majority of viable users must be left un-attacked. However, building an accurate classifier requires many viable samples. This suggests that at very low densities certain attacks pose no economic threat to anyone, even though there may be many viable targets. Most work on vulnerabilities ignores this fundamental question.

Thinking like an attacker is a skill rightly valued among defenders. It helps expose vulnerabilities and brings poor assumptions to light. We suggest that thinking like an attacker does not end when a hole is found, but must continue (as an attacker would continue) in determining how the hole can be monetized. Attacking as a business must identify targets, and this is easy only if we believe that attackers have solved a problem that has vexed multiple communities for decades.

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