

That Ain't You: Blocking Spearphishing Emails Before They Are Sent

Gianluca Stringhini[§] and Olivier Thonnard[‡]

[§]University College London
g.stringhini@ucl.ac.uk

[‡] Amadeus
olivier.thonnard@amadeus.com

Abstract

One of the ways in which attackers try to steal sensitive information from corporations is by sending *spearphishing* emails. This type of emails typically appear to be sent by one of the victim's coworkers, but have instead been crafted by an attacker. A particularly insidious type of spearphishing emails are the ones that do not only claim to come from a trusted party, but were actually sent from that party's legitimate email account that was compromised in the first place. In this paper, we propose a radical change of focus in the techniques used for detecting such malicious emails: instead of looking for particular features that are indicative of attack emails, we look for possible indicators of *impersonation* of the legitimate owners. We present IDENTITYMAILER, a system that validates the authorship of emails by learning the typical email-sending behavior of users over time, and comparing any subsequent email sent from their accounts against this model. Our experiments on real world email datasets demonstrate that our system can effectively block advanced email attacks sent from *genuine* email accounts, which traditional protection systems are unable to detect. Moreover, we show that it is resilient to an attacker willing to evade the system. To the best of our knowledge, IDENTITYMAILER is the first system able to identify spearphishing emails that are sent *from within an organization*, by a skilled attacker having access to a compromised email account.

1 Introduction

Companies and organizations are constantly under attack by cybercriminals trying to infiltrate corporate networks with the ultimate goal of stealing sensitive information from the company. Such an attack is often started by sending a *spearphishing* email. Attackers can breach into a company's network in many ways, for example by leveraging advanced malware schemes [21]. After entering the network, attackers will perform additional activities aimed at gaining access to more computers in the network, until they are able to reach the sensitive information that they are looking for. This process is called *lateral movement*. Attackers typically infiltrate a corporate network, gain access to internal machines within a company and acquire sensitive information by sending *spearphishing* emails. In a spearphishing attack an email is crafted and sent to a specific person within a company, with the goal of infecting her machine with an unknown piece of malware, luring her to hand out access credentials, or to provide sensitive information. Recent research showed that spearphishing is a real threat, and that companies are constantly targeted by this type of attack [38].

Spearphishing is not spam. While they may share a few common characteristics, it is important to note that spearphishing is still very different from traditional email spam. In most cases, spearphishing emails appear to be coming from accounts within the same company or from a trusted party, to avoid raising suspicion by the victim [40]. This can be done in

a trivial way, by forging the **From:** field in the attack email. However, in more sophisticated attacks, the malicious emails are actually sent from a *legitimate* employee’s email account whose machine has been compromised, or whose credentials have been previously stolen by the attacker [30]. From the attacker’s perspective, this modus operandi presents two key advantages. First, it leverages a user’s social connections: previous research showed that users are more likely to fall for scams if the malicious message is sent by somebody they trust [14]. Secondly, it circumvents existing detection systems, which are typically based on anti-spam techniques. This happens for two reasons: first, the content of spearphishing emails looks in many cases completely legitimate and it does not contain any words that are indicative of spam, since the goal is to make it resemble typical business emails. Second, if an email impersonating one of the company’s employees comes from that person’s computer, which has been compromised, then origin-based detection techniques, such as IP reputation, become useless. Secondly, it circumvents all IP and origin-based blacklisting systems, as well as email sender or domain verification systems such as *Sender Policy Framework* (SPF) and *DomainKeys Identified Mail* (DKIM) [19, 43], since the email is sent from a genuine email account.

A new paradigm for fighting targeted attack emails. Given how different spearphishing emails are compared to traditional spam and phishing emails, we propose a *paradigm shift* in detection approaches to fight this threat, and present IDENTITYMAILER, a system to detect and block spearphishing emails sent from compromised accounts. Instead of looking for signs of maliciousness in emails (such as words that are indicative of illicit content, phishy-looking content, or suspicious origin), IDENTITYMAILER determines whether an email was actually written by the author that it claims to come from. In other words, we try to automatically validate the genuineness of the email authorship. Our approach is based on a simple, yet effective observation: most users develop habits when sending emails. These habits include frequent interactions with specific people, sending emails at specific hours of the day, and using certain greetings, closing statements,

and modal words in their emails. The core of IDENTITYMAILER consists in building a user profile reflecting her email-sending behavior. When a user’s account gets compromised, the attack emails that are sent from this account are likely to show differences from the behavioral profile of the genuine user.

Behavioral anomalies can be very evident or more subtle. An example of a “noisy” attack is a worm that sends an email to the entire address book of a user [39], which is a behavior that typical users do not show. In more realistic scenarios, attackers might try to mimic the typical behavior of the person they are impersonating in their emails. What they could do is sending emails only at hours in which the user is typically sending them, and only to people she frequently interacts with, or even imitate the user’s writing style.

To make it more difficult for attackers to successfully evade our system, IDENTITYMAILER builds the email-sending behavioral profile for a particular user by leveraging both the emails previously sent by that specific user and a set of emails that other users in the organization authored. In a nutshell, IDENTITYMAILER compares the emails written by the user to the ones written by everybody else and extracts those characteristics that are the most representative of the user’s behavior. If common characteristics are shared by multiple users, however, these will be de-emphasized because they are not specific to a particular user. For example, certain functional words only used by a given user (and rarely by others) would model her behavior well.

When an attacker tries to learn a victim’s sending behavior to mimic it in his attack emails, he only has access to that user’s emails (since he compromised her account or personal machine). It is unlikely, however, that he has access to the ones authored by all other users within the company – besides the few emails exchanged by the victim and the coworkers he/she is interacting with. Therefore, all the attacker can do is learning the most common habits of the user (such as the email address that is more frequently contacted, and at what time the user generally sends emails), but he has no guarantee that those traits are actually representative of the victim’s behavior.

Working on the sending end. Traditional anti-

spam systems work on the receiving end of the email process. This means that they analyze incoming emails, and establish whether they are legitimate or malicious. This approach is very effective in general, but it has many drawbacks in our specific case. First of all, the analysis that can be performed on incoming emails has to be lightweight, due to the large amount of emails, mostly malicious, that mail servers receive [36]. As a second drawback, learning the typical behavior of a user on the receiving end has the problem that a mail server only has visibility of the emails that are exchanged between that user and people whose mailboxes are hosted on the server. Therefore, a behavioral profile built from these emails might not be representative enough to correctly model the sending habits of users.

Because of the aforementioned problems, we propose to perform the analysis when emails are sent, before they are forwarded to the outgoing SMTP server. Our approach builds a behavioral profile based on the emails that a user sent in the past (and a set of emails authored by the other people in the organization). Then, every time an email is sent by that account, our approach checks if this email matches the profile learned for the real account's owner. If the email does not match the learned profile, we consider it anomalous. The account might have been compromised, and the email might actually be an attack attempt. However, the anomaly might also be a false positive. Perhaps the user is working on a deadline, and is sending emails late at night, or is sending a personal email, and using a colloquial language, while the account is primarily used to send work-related emails.

False positives are a big problem in traditional anti-spam systems, because they annoy users in the best case, and they prevent them from receiving important emails in the worst case. Luckily, the fact that our approach operates on the sending side of the email process comes to our aid. Any time an email is flagged as anomalous, we can start a process to verify the identity of a user. In our design, this process would include sending a confirmation code to a device owned by the user, as part of a two-factor authentication scheme [4]. If the user correctly inputs the confirmation code when asked we consider

the anomaly as a false positive, and the email is forwarded. In addition, we update the user's behavioral profile to include this particular email, so that we will avoid similar false positives in the future. If the user fails at solving the challenge, however, we consider the email as a possible attack, and we discard it. We acknowledge that having to go through an identity-verification process can be annoying for users. However, we think that having users confirm their identity once in a while is a fair price to pay to protect a company against advanced email attacks, as long as the verifications are rare enough (for example, one in every 30 emails on average).

We tested IDENTITYMAILER on a large set of publicly-available emails, and on real world data sets made of malicious targeted emails sent to the customers of a large security company.

In summary, this paper makes the following contributions:

- We propose a new approach to detect spearphishing emails sent from compromised accounts: instead of looking for signs of maliciousness, we introduce a set of features that are representative of the email-sending behavior of a user, and propose a method to check emails against the learned sending behavior (*i.e.*, email authorship validation).
- We implemented the approach in a system called IDENTITYMAILER, which was tested against a large dataset of publicly-available emails, as well as other real-world datasets of targeted attack emails. Our experimental results show that our approach can effectively block spearphishing emails that state-of-the-art systems failed to detect with a detection rate above 90% for users with a *sent* history of only 1,000 emails. In contrast, existing systems that look for signs of maliciousness are failing to detect most of these advanced email attacks.
- We show that having access to the emails sent by the victim is not sufficient to evade IDENTITYMAILER, and that imitating the most common characteristics present in those emails can even

augment the chances of being detected by the system.

2 Threat Model

Spearphishing can be broadly defined as targeted phishing. In traditional phishing emails, attackers pretend to be operators from online services such as Online Social Networks or Online Banking Portals, and lure their victim into inserting their credentials on a fake web page that reproduces the home page of that online service. An example of phishing email is shown in Figure 1. A spearphishing email is a type of phishing email for which the attacker collected some information about the victim, and included it in the attack email to make it more believable [24].

A spearphishing attack can be more or less sophisticated. An example of an attack with a low sophistication is a password reset request for a corporate service sent to all the employees of a company. In this case, the only difference with a traditional phishing email is that, unlike phishing attempts against common online services, all people receiving the malicious email supposedly have an account on the corporate service. A more sophisticated spearphishing attack is one that targets a specific person within a company, and leverages personal information about that person in order to make the email look even more convincing. Attacks of such sophistication can usually be detected by variations of traditional anti-spam and anti-phishing techniques. For instance, the attack email might be coming from an IP address that does not belong to the online service that it is allegedly coming from; similarly, the URL of the link in the phishing email might not be hosted on the domain of the online service. Systems that look at the source IP address of an email [1, 26, 27] or at the actual phishing web page [9, 46] are able, in general, to detect such attacks.

Although existing anti-spam and anti-phishing techniques can be adapted to detect certain types of spearphishing attacks, as the attacker gets even more sophisticated, these techniques become inadequate in fighting this threat. Consider, for example, the spearphishing email in Figure 2. In this case, the

```
Received: from [FOREIGN IP]
From: <support@site.com>
To: <victim@company.com>

Dear user ,
Your account has been hacked.
Please reset your password
<a href="http://fakesite.org">
here </a>
```

Figure 1: Example of a traditional phishing email. The source IP address does not belong to the online service that the email claims to come from, and the URL points to a phony web site.

attacker managed to compromise the email account of one of the company’s managers, and is using it to send an email to a member of his team. In the attack email, the attacker asks the victim to send his boss a copy of the latest report. The victim is very likely to fall for this attack because there is nothing indicative of a malicious email: the email is coming from the email account of the manager, and therefore the IP address is the correct one; similarly, the language of the email is not suspicious at all, because the language used is typical of regular business emails. In addition, since the attacker has access to the manager’s email account, he can retrieve the report directly from there, once the victim sends it, and does not need to include the link to an external web server in the spearphishing email. From the perspective of traditional anti-spam and anti-phishing techniques, the email in Figure 2 looks perfectly authentic, and has no indicators for being flagged as anomalous.

In this paper, we propose a technique that can detect sophisticated spearphishing emails that do not present any signs of maliciousness. As we said, our approach works as follows: first, we learn the typical behavior of a user based on his sent email history; then, we compare each new email sent from that user account to determine if it does match the learned behavior. In the following sections, we describe our approach in more detail.

```

Received: from [COMPANY IP]
From: <manager@company.com>
To: <victim@company.com>

Dear <victim>,
As discussed during our meeting,
please send me the latest report.
The template to use is attached.

Thanks,
<manager>

```

Figure 2: Example of advanced spearphishing email. The sender account has been compromised, therefore the sender IP address is not anomalous. Also, the content of the email does not look anomalous: the language used looks like regular business emails.

3 Behavioral Profiles

In the very first stage, IDENTITYMAILER must accurately learn and model the email-sending behavior of a user, as it will enable us to perform better detection of anomalous emails in a later stage. However, defining user-specific traits that best distinguish a user’s sending behavior is not trivial. To determine these traits, IDENTITYMAILER requires two datasets: a set \mathbf{M}_u of emails written by a user U and a set \mathbf{M}_o of legitimate emails written by other people. By comparing the emails in \mathbf{M}_u to the ones in \mathbf{M}_o , we can extract the distinguishing characteristics of the email-sending behavior of U .

\mathbf{M}_o should be composed of both emails sent by people working in the same organization as U , as well as of emails written by people who are completely unrelated to U . As we will explain later, the privacy concerns of our approach are minimal, because we do not save the full email, but only a feature vector associated to it. On one side, having \mathbf{M}_o built from the emails sent by the users working in the same organization as U helps in giving less importance to common characteristics shared by coworkers. For example, if no user in the organization ever sends emails on Sundays, it is less peculiar

if the user follows this trend. On the other hand, having emails sent by users who are completely unrelated to U in \mathbf{M}_o helps giving to the model examples of behavioral characteristics that are uncommon in the organization, but common outside of it. We provide a more detailed description on how we build \mathbf{M}_o in Section 3.2. By using only legitimate emails to build our behavioral profiles, IDENTITYMAILER does not need to have ever observed any attack email to perform detection, similarly to what happens with traditional anomaly-detection systems. This is important, because it makes our approach independent from specific attack schemes.

To build the email-sending behavioral profile for a user, we proceed in two steps. First, we extract a number of features for each email in \mathbf{M}_u and \mathbf{M}_o . As a second step, we leverage these feature vectors to build a classification model, which represents the actual behavioral profile. We use this profile to analyze any email written by the user, and determine whether it was really written by that user.

3.1 Extracting Behavioral Email Features

We define three classes of email features, which pertain to: *writing habits*, *composition habits*, and *interaction habits*. Previous research showed that authorship identification is possible by looking at stylometry features (which are a subset of what we call writing habits) [6]. However, these approaches rely on texts of a certain length (250 words or more) [10]. Unfortunately, as we show in Section 5, many emails are short. If our approach relied only on the writing habits of a user (i.e., stylometry features), it would fail at detecting short attack emails. Therefore, we need additional information to deal with such emails, as described here after. In the following, we describe the features that our approach uses to characterize an email.

Writing habits. People normally develop their own writing style. For example, some people use certain functional words (such as “although”) more often than others, or write dates in a certain way. Analyzing a user’s style has been used in the past to determine authorship of texts and emails [2, 6, 23]. Simi-

larly, we consider a user’s writing style as a strong indicator of email authorship. An attacker could, in principle, learn the characteristics of his victim’s style, and replicate them in the attack emails that he sends. However, previous research showed that imitation of another person’s writing style is detectable most of the time [3]. In addition, as we will show in Section 5.4, it is difficult for an attacker to figure out which features are the most representative of a user’s writing style. In the following, we define a number of features that help defining a user’s writing style. The complete list of writing-habit features used by IDENTITYMAILER can be found in Table 1.

1) *Character occurrence (62 features)*. These features represent how often a character, or a set of characters, appear in the email text. Given a set of characters \mathbf{C} and an email text M , we define the character occurrence of \mathbf{C} in M o_c as the number of times that any of the characters in \mathbf{C} occur in M , divided by the length of M . Examples of character occurrence features include the frequency of alphabetical letters (such as “a”), the frequency of certain punctuation signs (such as “;”), and the frequency of sets of characters (such as capital letters or cardinal numbers).

2) *Functional word occurrence (344 features)*. These features represent how often the person uses specific functional words. We define as functional words those words that do not serve to express content, but instead are used to express grammatical relationships with other words within a sentence. These include adverbs (such as “when”), auxiliary verbs (such as “is”), and prepositions (such as “for”). Some of these features are useful to determine whether a user uses certain functional words in their extended or shortened form, and to what extent (for example, whether she usually uses “don’t” instead of “do not”). Given a word FW and a set of words \mathbf{W}_m in an email, we calculate the word occurrence o_{fw} in \mathbf{W}_m as the number of times FW occurs in the email, divided by the size of \mathbf{W}_m .

3) *Special word occurrence (11 features)*. These features represent how often a user uses certain “special” words in her emails. Special words include full names, dates, and acronyms. Given a regular expression R_{sw} representing the special word, an email M , and a set \mathbf{W}_m containing the words in M , we cal-

culate the special word occurrence o_{sw} of R_{sw} as the number of matches in M for R_{sw} , divided by the size of \mathbf{W}_m .

4) *Generic style characteristics (38 features)*. These features represent generic characteristics of the style of a user. Examples include the type of bullets that the user uses in lists (“1-”, “1.”, or others), whether she uses a comma as a separator for large digits or not, and whether she uses a space after punctuation. Given a set of regular expressions \mathbf{R}_{sc} representing a style characteristic, an email M , and a set \mathbf{W}_m containing the words in M , we define the style characteristic s_c as the number of matches of the regular expressions in \mathbf{R}_{sc} in the email M , divided by the size of \mathbf{W}_m .

5) *Style metrics (33 features)*. These features capture information about the style of entire emails. Some features are rather simple, such as the number of paragraphs in the email. Others are more advanced, and depict the expressiveness of the language used in the email. Examples are the *Sichel measure* or the *Yule metric*, which describe how complex the vocabulary used by an author is. These metrics have been already used in previous work on authorship identification [41, 44].

6) *Context-specific words (variable number of features)*. These features look for occurrences of words that are common in a certain industry. People working in that industry will use them more or less frequently, depending on their role in the company and their specific job. Examples of context-specific words for a financial institution include the words “stock”, “asset”, and “contract.” Given a word W and a set of words \mathbf{W}_m in an email, we calculate the context-specific word occurrence o_{wcs} as the number of occurrences of W in \mathbf{W}_m , divided by the size of \mathbf{W}_m . Context-specific words vary with the type of business that the company is doing, and have been used in other authorship-recognition research [47]. We discuss the choice of context-specific words that we used in our experiments in Section 5.2.

Composition and sending habits. Other habits that users develop regarding their email-sending behavior pertain to the way of composing emails. In the following, we describe this type of features. A complete list of composition-habit features can be found

Character occurrence

Punctuation

. : ; , ' " ? !

Special characters

% _ & \$ @ * \ ` i # / -

Parenthesis

() [] {}

Ordinals

0123456789

Capital letters

ABCDEFGHIJKLMNOPQRSTUVWXYZ

Functional words

a	aboard	about	above	absent	according to	across	after
against	ahead of	all	along	alongside	amid	amidst	although
am	among	amongst	and	another	any	anybody	anyone
anything	are	aren't	arent	are not	around	aint	ain't
around	as to	as far as	as well as	as	aside from	're	aslant
astride	ah	at	athwart	atop	because	because of	been
before	behind	believe	below	beneath	besides	beside	best
between	be	beyond	both	but	by means of	by	can not
cannot	can't	can	cant	can you	close to	concerning	considering
cause	cos	could	despite	did not	didn't	didnt	did
do	does	do not	don't	dont	down	due to	during
each other	each	either	enough	even if	even though	even	everybody
everyone	everything	every	except for	except	far from	few	following
for	from	had not	hadnt	hadnt	had	have	ahead to
he	herself	hers	her	himself	him	his	I believe
hi	hello	happy	take care	regards	please	greetings	cheers
I'd	if	I'll	in accordance with	in addition to	in case	in case of	including
in front of	in lieu of	in order that	in order to	in place of	inside of	inside	in spite of
instead of	instead	in to	into	in	is	it	I
latter	less	like	little	look	lots	many	may
me	mid	might not	mightn't	mightnt	might	mine	minus
more	most	much	must not	mustn't	must not	mustnt	must
myself	my	near to	near	need	neither	next to	next
nobody	none	no one	nope	nor	nothing	notwithstanding	no
now that	off	of	okay	OK	on account of	on behalf of	once
one another	one	on to	on top of	onto	on	opposite	or
others	other	ourselves	our	out from	out of	outside of	outside
out	over	owing to	own	past	per	please	plenty
plus	prior to	pursuant to	quite	regarding	regardless of	round	same
seem	several	shall not	shall	shan't	shant	she	should not
shouldn't	shouldnt	since	somebody	someone	something	somewhere	some
soon	so	subsequent to	such	take care	thanks	thank you	than
that	the	theirs	their	themselves	them	then	these
they	think	this	those	though	throughout	through	till
towards	toward	to	under	unless	unlike	until	upon
up	used	us	versus	via	was not	wasn't	wasnt
was	we	were not	weren't	were	was not	what	whatever
when	whereas	where	whether or not	whether	which	whichever	while
who	whoever	whomever	whom	whose	will	will not	with
within	without	won't	wont	worth	would	yes	yet
you	yourself	yourselves	yours	your			

Special word occurrence

Full name	date	day of the week	shortened day
month	shortened month	year	phone number
dollar amount	time of the day	fraction	

Generic style characteristics

Emoticons	:) :-) :P :-P :(:-(:/ :-/		
Bullets type 1	1) 2) 3) ...		
Bullets type 2	1- 2- 3- ...		
Bullets type 3	1. 2. 3. ...		
Bullets type 4	(i) (ii) (iii) ...		
Bullets type 5	first second third ...		
Bullets type 6	- ...		
Programming language keywords	if then else while do switch case return		
comma separated list	oxford comma	signature	no space after punctuation
no comma in large digits	comma in large digits		

Style metrics

number of paragraphs		sentences per paragraph	unique words	number of words	message length
number of long lines		number of short lines	frequency of words of length N (from 1 to 20)		
hapax legomena		hapax dislegomena	Sichel's S measure		Honore's R measure
Yule's metric		Simpson's metric			

Context-specific words

account	accounting	attach	attached	attachment	authorize	authorizing	bank
candidate	cash	capacity	consideration	contract	detail	derivative	document
email	e-mail	Enron	equity	fax	financial	flow	gas
increase	information	item	manage	market	oil	option	potential
recommend	reserve	review	risk	scan	section	send	sent
stock	supply	target	trader	trading	trip		

Table 1: List of writing-habit features used by IDENTITYMAILER.

Message characteristics:	has signature	has URL
	indented lines	quoted lines
	original attached	has attachment
	is reply	is forwarded
	has HTML	n. of recipients
	n. of ccd users	
Time characteristics:	hour of the day (24 features)	
	day of the week (7 features)	
URL characteristics:	points to domain (variable # of features)	

Table 2: List of composition-habit features used in our approach.

in Table 2.

1) *Message characteristics (11 features)*. These features capture specific user habits in email composition. Examples of such habits are including the original email at the end of a reply, including quotes to the original email interleaved with the text, or adding a signature at the end of the email. Message-characteristic features are boolean, meaning that they are set to 1 if a certain behavior is present in an email, and to 0 otherwise.

2) *Time characteristics (31 features)*. Users tend to send emails at specific times of the day, and only during specific days. For example, most people working in an office will send emails between 9 am and 5 pm, from Monday to Friday. Given this observation, an email sent at midnight on a Saturday might be suspicious. These features keep information about when an email has been sent. In particular, they look at the day of the week and at the hour at which the email was composed. Similarly to other composition-habit features, time-characteristic features are boolean. We define seven features for the days of the week, and 24 features for the hours of the day.

3) *URL characteristics (variable number of features)*. Some users include URLs in their emails, such as links to web pages that are needed for their job, or to websites that they consider interesting. Over time, the set of URL domains that a user includes in her emails tends to be limited [8]. On the other hand, if the user sent an email with a URL pointing to a domain that she has never included before, this might be considered as suspicious.

To instantiate URL-characteristic features, we need a set of domains \mathbf{L}_u that the user, as well as other people in her organization, referenced in the past. This helps identifying resources that are “internal” to the organization (which should be referenced often in the company’s emails). We also include an “*other*” category to take into account those domains that were never referenced by anybody in the organization. Similarly to the other composition-habit features, URL-characteristic features are boolean, and are set to 1 if that domain is referenced in the email, and 0 otherwise.

Interaction habits. The last type of features involves the social network of a user. Users typically send a large deal of emails to a handful of contacts, usually coworkers or close friends. Having an email sent to an address that was never contacted before might thus contribute to the suspiciousness degree of an email, especially if the user under scrutiny does not usually interact with many other users.

To characterize the social network of a user, we look at the recipients email addresses (the **To:** field), as well as at *carbon copy* addresses (the **CC:** field). We define four types of interaction-habit features, representing the email addresses and domains that a user sends emails to. The *recipient address list* features take into account the email addresses that an email is addressed to, while the *recipient domain list* ones look for the domains that those email addresses belong to. The idea behind this distinction is that if a user sends an email to an address that she has never referenced before, but that belongs to an or-

ganization that she often interacts with, this is less suspicious than an email addressed to a completely unknown domain. Similarly, we define a *carbon copy address list* and a *carbon copy domain list* by analyzing the email addresses of the **CC:** field.

To instantiate the interaction-habit features, we need a list \mathbf{L}_a of email addresses that the user, as well as the other people in the same organization, contacted in the past. It is important to look at the email addresses that the user has never contacted, but some of her coworkers have. This is because having a user sending an email to an executive she has never contacted before is very suspicious, and might be a sign of spearphishing. In addition, to account for those addresses and domains with which nobody in the organization has interacted before, we add, for each of the four feature types, an “*other*” category. Similarly, we leverage a list \mathbf{L}_d of domains to which the users in the organization have written emails in the past.

Interaction-habit features are boolean: they are set to 1 if an email is addressed to the address (or domain) represented by a given feature, and to 0 otherwise. If, for any of the four feature types, all features of that type have a value of 0, the “*other*” feature is set to 1.

3.2 Building Users Behavioral Profiles

After extracting a feature vector for each email that a user sent, we leverage them to build a behavioral model that is able to distinguish whether an email has likely been sent by that user or not. To learn the distinguishing characteristics of the email-sending behavior for a user U , IDENTITYMAILER compares the feature vectors built from the emails sent by the user (\mathbf{M}_u) to the feature vectors built from a set of legitimate emails sent by other people (\mathbf{M}_o). The challenge in picking \mathbf{M}_o is to select a set of emails that is representative enough to make the most characteristic features of the behavior of the user stand out.

Given a user U who wrote a set of emails \mathbf{M}_u , we pick the set of emails \mathbf{M}_o as follows. For each user U_i in the organization (other than U), we keep a set of emails that U_i has sent in the past. We call

this set \mathbf{M}_{ui} . In addition, we consider a “special” user U_x . The set of emails \mathbf{M}_{ux} corresponding to the user U_x consists of emails that were not written by the users in the organization. This set of emails could be a subset of the emails that were received by the company’s mail server, or a set of publicly-available legitimate emails. Then, for each email in \mathbf{M}_u , we pick a random email written by another user U_i and add it to \mathbf{M}_o . We change the user U_i for each email in \mathbf{M}_u , in a round-robin fashion. By doing this, we ensure that the distribution of emails written by different users in \mathbf{M}_o is uniform.

After having collected \mathbf{M}_u and \mathbf{M}_o , IDENTITYMAILER’s classifier is trained to learn the email-sending behavioral profile of user U . To this end, we leverage Support Vector Machines (SVMs) trained with Sequential Minimal Optimization (SMO) [25]. The SMO algorithm is an iterative algorithm used to efficiently solve the optimization problem required for training SVMs. More details are provided in Section 5.2.

Since the email-sending behavior of a user is likely to slightly change over time (for example, as the user makes new social connections), IDENTITYMAILER keeps updating the behavioral profile, by adding to the profile the new emails that the user sends. The identity verification mechanism described in Section 4.1 ensures that the emails we add to the behavioral profile have been genuinely written by the user. Being able to constantly update a user’s behavioral profile is important because it gets more accurate as the number of emails sent by the user increases. However, the strength of the model also depends on how consistent a user is in her email-sending habits. As we will discuss in Section 5.2, the features that we defined all contribute in defining the email-sending behavior of a user. The weight of the different features actually depends on each user’s specific habits, and cannot be generalized. In addition, some features are easier for an attacker to imitate than others. For example, it is easy for an attacker to emulate the functional words that are most used by a user. However, the more advanced style metrics, such as the *Sichel measure*, are not as easy to emulate. In any case, as we will show in Section 5.4, it is difficult for an attacker to figure out which features he should

imitate to evade detection by our approach.

4 Detecting Anomalous Emails

After having built the email-sending behavioral profile for a user, our approach checks any email that the user is sending against his profile. More specifically, our algorithm works as follows:

Step 1: For each email M that user U sends, we extract a feature vector \mathbf{V}_m .

Step 2: We compare \mathbf{V}_m against the behavioral profile of U , which we call \mathbf{BP}_u . If \mathbf{V}_m complies with \mathbf{BP}_u , we validate the email as being written by U , and proceed to step 4. Otherwise, we consider M as anomalous, and go to step 3.

Step 3: To verify that the email was written by the legitimate user U , we perform an identity verification. If U correctly confirms her identity, M is considered as a false positive, and we go to step 4. If U fails to confirm her identity (or decides not to, because she may recognize an ongoing attack), the email is considered as malicious and is discarded. A notification may then be sent to an administrator for further investigation. In the next section, we describe how we envision the identity verification process to take place.

Step 4: We add \mathbf{V}_m to the set of feature vectors that are used to calculate \mathbf{BP}_u . This information will be used the next time that the behavioral profile is updated.

It is not necessary to update the behavioral profile for a user for every sent email. The reason is that, although the email-sending habits of a user change over time, they do not change that fast. In addition, updating the behavioral profile for a user may require up to 30 seconds in the current implementation. For these reasons, we envision the behavioral profile update as a batch process that could be performed daily or weekly.

4.1 Verifying a User’s Identity.

One of the main challenges that anti-spam systems have to face are false positives. Flagging a legitimate

email as spam has a high impact on the user, because it might prevent her from seeing that email at all. This is due to traditional anti-spam techniques operating on the receiving side of the email process, where it is impossible to verify that the sender of an email is who she actually claims to be. In contrast, operating on the sending side enables us to request the user to prove her identity when a certain email is looking suspicious, before emails are actually sent.

In our approach, we propose to perform an identity verification process by sending, for example, a confirmation code to a device controlled by the user, and request the user to input that code as part of a two-factor authentication process [4]. This verification process might be a simple method such as answering a security question or a more advanced method, such as a text message sent to the user’s mobile phone as part of a two-factor authentication process [4]. Each method has advantages and disadvantages. However, analyzing the single identity-verification methods that one could implement goes beyond the scope of this paper. For our purposes, we just assume that by going through this process the user can prove her identity with high confidence.

We are aware that having to go through an identity verification process might be an annoyance for users. However, there is always a trade-off that needs to be established between usability and security. So, we argue that if the number of validations that a user has to go through is reasonably low, it is a fair price to pay to significantly increase the security of a company. In Section 5.2 we perform an analysis by which we show that the number of identity verification processes required by IDENTITYMAILER is reasonably low, and probably acceptable for a user’s perspective.

5 Evaluation

In this section, we evaluate the effectiveness of IDENTITYMAILER. First, we describe the evaluation datasets that we used in our experiments. Then, we perform an analysis of the classifier used to build the email-sending behavioral profiles. We show that the behavioral profiles build by IDENTITYMAILER are

effective at detecting attack emails sent by compromised accounts. Also, we analyze the resilience of our system to “mimicry” attacks and show how IDENTITYMAILER is able to deal with and detect this type of advanced attacks.

5.1 Evaluation Datasets

To evaluate IDENTITYMAILER we leverage a number of email datasets. First, we leverage the *Enron corpus* [18] as a large dataset of legitimate emails. This publicly-available dataset contains the emails sent by the executives of a large company over several years. The dataset comprises 148 users, accounting for 126,075 emails. The Enron dataset is representative of the type of emails sent in a large corporation (in terms of sending times, language, interactions), and this makes it suitable for our testing purposes. In the remainder of the paper, we call this dataset \mathbf{D}_1 . As a second dataset of legitimate emails we use a set of emails that were provided to a large security company by their customers for research purposes. This dataset is made of 1,776 emails which we consider as useful to complement \mathbf{D}_1 because of their diversity. In particular, they are useful to populate \mathbf{M}_{ux} , as we explained in Section 3.2. We call this dataset \mathbf{D}_2 . We use the datasets \mathbf{D}_1 and \mathbf{D}_2 for training. In particular, for each user in \mathbf{D}_1 , we build an email-sending behavioral profile, by leveraging both the emails in \mathbf{D}_1 and in \mathbf{D}_2 .

For testing purposes, we needed a number of emails sent from compromised accounts, and preferably used as part of a targeted attack. The problem is that, unlike regular spam, collecting a large amount of such emails is challenging. To overcome this problem, we manually selected three datasets of malicious emails. These emails come from a set of malicious messages detected by a large security company, which were submitted by their customers for manual analysis and validation.

The first dataset, that we call \mathbf{S}_1 , is composed of generic spam emails. Such emails typically advertise goods or services, such as stock trading, pharmaceuticals, and dating sites. The main difference between the emails in \mathbf{S}_1 and common spam is that a state-of-the-art system failed in detecting them as mali-

cious, and therefore we can consider them as “hard” to detect; we test IDENTITYMAILER on this dataset to show that although the system has not been designed to fight traditional spam, it performs well in detecting it, in case it was sent by compromised email accounts. \mathbf{S}_1 is composed of 43,274 emails.

The second dataset, that we call \mathbf{S}_2 , is composed of malicious emails (mostly phishing scams) that were sent by email accounts that had been compromised. We selected these emails by looking at emails in \mathbf{S}_1 that were malicious, but that had valid DKIM and/or SPF records [19, 43]. In total, \mathbf{S}_2 contains 17,473 emails.

The third dataset, which we call \mathbf{S}_3 , is a dataset of more sophisticated spearphishing emails. Such emails try to lure the user into handing out corporate-specific sensitive information (such as access credentials, confidential documents, etc) to a malicious party, usually via social engineering. As we said, spearphishing emails are particular insidious to companies, because it can lead to high financial losses. \mathbf{S}_3 contains 546 emails. These emails went undetected by the defense systems deployed by the security company, and were submitted by its customers after the attacks had happened. The emails in \mathbf{S}_2 and \mathbf{S}_3 closely resemble the threat model that we are trying to counter with IDENTITYMAILER. In the next sections, we leverage these datasets to evaluate the effectiveness of IDENTITYMAILER. First, we investigate how representative of a user’s behavior the behavioral models built from \mathbf{D}_1 and \mathbf{D}_2 are. Then, we leverage these behavioral models to see whether IDENTITYMAILER would have detected an anomaly, in case any of the users sent a malicious email from \mathbf{S}_1 , \mathbf{S}_2 , or \mathbf{S}_3 . As a last experiment, we investigate how easy would be to evade IDENTITYMAILER by imitating a user’s email-sending behavior. We do this by modifying the emails in \mathbf{S}_1 , \mathbf{S}_2 , and \mathbf{S}_3 to look more and more similar to each user’s sending behavior.

5.2 Analysis of the Classifier

We start by describing how we selected the features used in IDENTITYMAILER to build behavioral user profiles. Then, we investigate how accurate these

profiles are to determine the true authorship of an email. Finally, we show that the writing habits are usually not sufficient to detect whether an email is forged or not.

Instantiation of the features. As we explained in Section 3.1, some of the features used by our approach are specific to the organization in which the system is run. In particular, we need to know which email addresses and domains have been contacted previously by the users within an organization, as well as the domains that have been referenced in the body of the emails, as part of the URLs. We leverage the dataset \mathbf{D}_1 to calculate the sets \mathbf{L}_u , \mathbf{L}_a , and \mathbf{L}_d . For this particular dataset, \mathbf{L}_u was composed of 595 domains, \mathbf{L}_a of 22,849 email addresses, and \mathbf{L}_d of 3,000 domains. Notice that, in a production environment, the size of \mathbf{L}_u , \mathbf{L}_a , and \mathbf{L}_d would increase over time, since the users in the company would post more URLs, and contact new people. This means that the number of features used by IDENTITYMAILER increases over time as well. We argue that this is not a problem. Our experiments on \mathbf{S}_1 , which we omit for space reasons, show that the set of different domains that a user contacts in her emails over time grows slowly.

As for the writing-habit features, we needed to select a set of context-specific words. We did this manually, by analyzing the most common words in the emails of \mathbf{D}_1 and picking those words that are specific of the business of the company (i.e., finance, oil, and human resources). In total, we selected 46 context-specific words, which are listed in Table 1. We acknowledge that this process could be automated, but the manual selection worked well for our purposes, and previous author-identification work used a similar approach [47].

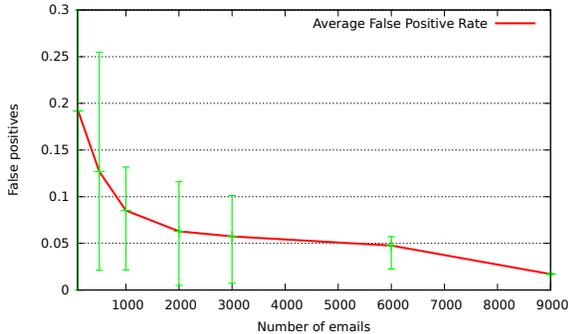
Accuracy of the classifier. To evaluate to what extent the IDENTITYMAILER profiles are truly representative of the sending behavior of users, we proceeded as follows. First, for each user U in \mathbf{D}_1 , we extracted the sets \mathbf{M}_u and \mathbf{M}_o for that user, following the algorithm described in Section 3.2. As said before, we use the emails sent by U as positive examples, and a mix of emails from \mathbf{D}_1 and \mathbf{D}_2 as negative examples. In this experiment, we consider IDENTITYMAILER to make a correct classification if it attributes an email

authored by a user U to that user, and an incorrect classification otherwise.

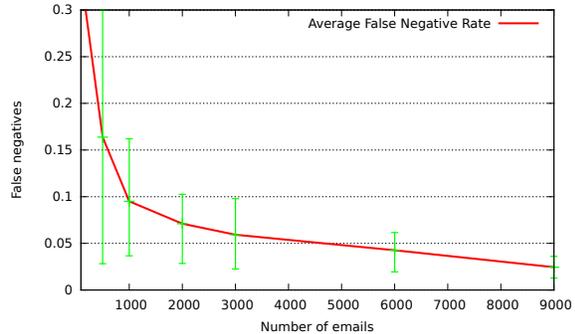
After having trained the system for each user, we performed a 10-fold cross validation on them to investigate the accuracy of the behavioral profiles. The 10-fold cross validation gives us an idea of how the system would behave in the wild, while encountering previously-unseen emails. In particular, it gives us an estimate of how many emails would be incorrectly flagged as malicious because of a change in behavior by a given user, as well as how many attack emails would actually be missed by IDENTITYMAILER. In this experiment, a false positive would indicate an email that was authored by the user, but flagged by IDENTITYMAILER as anomalous. In this case, an identity verification process would be started, by which the genuine user would have correctly confirmed her identity. We want the number of false positives to be low, because having to confirm one’s identity too often would become a users’ annoyance. Conversely, a false negative would indicate a forged email missed by IDENTITYMAILER, thus mistakenly attributed to the legitimate user. We want false negatives to be as low as possible, since in a real scenario, each of them would correspond to an attack that went undetected.

Intuitively, there are two factors that influence the robustness of a user’s behavioral profile. The first factor is the number of emails that a user has sent in the past. Having a larger number of examples of a user’s sending style and habits makes the model more representative and less prone to false positives and false negatives. The second factor is how consistent is the sending behavior of a user. A user always sending emails in the morning, to a limited set of recipients, will obviously be a lot more easily recognizable than a user who uses her account for both professional and personal use and quite frequently sends emails at night.

The number of emails sent by users in \mathbf{D}_1 varies substantially. On average, every user in \mathbf{D}_1 has sent 840 emails, with a standard deviation of 1,345. The largest number of emails sent by a user in \mathbf{D}_1 is 8,926. The accuracy of IDENTITYMAILER increases significantly as the number of emails sent by a user increases, because the system can learn the typical



(a) Analysis of the False Positive rate



(b) Analysis of the False Negative rate

Figure 3: Analysis of false positives and false negatives on the ten-fold cross validation. The X-axis shows the number of emails that a user has sent in the past. As it can be seen, both false positives and false negatives decrease as the user’s *sent* email volume increases.

behavior of that user more accurately. It is challenging to show how the system behaves in a figure, because any time the history of emails sent by the user increases, we are evaluating a new system; for this reason, a Receiving Operating Curve (ROC) is not suited to represent the accuracy of IDENTITYMAILER. In Figure 3 we represent the average rate of false positives and false negatives according to the *sent* email volume of a user. As Figure 3 shows, the accuracy of the email-sending behavioral profile built by IDENTITYMAILER increases as the user sends more emails. The error bars in the figure show that the accuracy of a behavioral profile does not only depend on the email volume, but also on the user’s style and habits. For users who have consistent habits, IDENTITYMAILER can achieve almost zero false positives and false negatives. On the other hand, certain users having more variable habits end up having higher rates of false positives and false negatives than the average. However, this variability is reduced as the number of emails sent by the user increases.

Figure 3a shows the average number of false positives generated during the 10-fold cross validation, broken down by the amount of emails sent in the past by each user. As explained before, a false positive in this context would result in the user being required to go through an identity verification mechanism. We note that, on average, a user who has sent at least 1,000 emails would have to confirm her iden-

tity for 1 in 12 emails. By increasing the sent email volume, a user who sent at least 8,000 emails would have to confirm her identity on average for 1 in 58 emails that she sends. Given the average number of emails that a typical corporate user sends nowadays — 33 per day, according to a recent report [37], reaching this amount of interaction history would not take a long time. Moreover, these are average numbers, thus users with a more stable email-sending behavior can already reach 2% false positives after having sent only 1,000 emails. These users would then have to go through the identity verification process for only 1 in every 50 emails that they send. We argue that these numbers are reasonably low and quite acceptable in a corporate environment, where the hassle of confirming a user’s identity is largely compensated by a significantly higher user protection against identity and IP theft.

Similarly, Figure 3b shows the number of false negatives for the 10-fold cross validation. As it can be seen, a sent history of 1,000 emails enables IDENTITYMAILER to build a model able on average to block 90% of the forged emails. Recall improves as the number of sent emails increases. The behavioral profile of a user who sent at least 8,000 emails has an average recall of 96%. A careful reader might notice that the accuracy of IDENTITYMAILER might be slightly under current state-of-the-art anti-spam systems. However, as we previously said, the purpose

of our system is very different from anti-spam techniques. We want to ensure that no malicious email is sent illegitimately on behalf of a user, and current anti-spam techniques were not designed to deal with such attacks.

Analysis of the features. Previous research showed that it is possible to identify the author of an email just by looking at stylometric features (what we refer to as *writing habits* in this paper) [6]. However, Forsyth et al. showed that such approaches are only reliable in the presence of a consistent amount of text [10]. In particular, they identified the minimal amount of text required for stylometry-based author identification to become reliable (which is about 250 words). Unfortunately, 78% of the emails in \mathbf{D}_1 are under this size limit. In particular, 50% of the emails in that set are shorter than 100 words.

As we said, to deal with this issue of short email length, we use two other classes of features: *composition habits* and *interaction habits*. We wanted to investigate the contribution of these features in detection accuracy, and confirm that writing-habit features alone are not sufficient. To achieve this, we performed the 10-fold cross validation that we ran to evaluate the classifier again, but this time we only used writing-habit features. The results show that writing-habit features alone are indeed failing to obtain an accurate detection. For a user with a 1,000 sent emails history, the average number of false positives is now 22% – almost three times higher than for the full-fledged classifier. The lowest rate of false positives obtained in this case is for users having sent at least 8,000 emails, yet the FP-rate is still around 9.8% – almost six times higher than the rate obtained with the full-fledged classifier. Clearly, while stylometry-based methods might be useful in forensic cases, they are not sufficient in this case to determine, with high confidence, whether an email has been sent by an attacker or not.

5.3 Detecting Attack Emails

We now evaluate IDENTITYMAILER on the attack datasets \mathbf{S}_1 , \mathbf{S}_2 , and \mathbf{S}_3 . First, we created the email-sending behavioral profiles for each user U in \mathbf{D}_1 , as explained in Section 3.2. Then, for each email in \mathbf{S}_1 ,

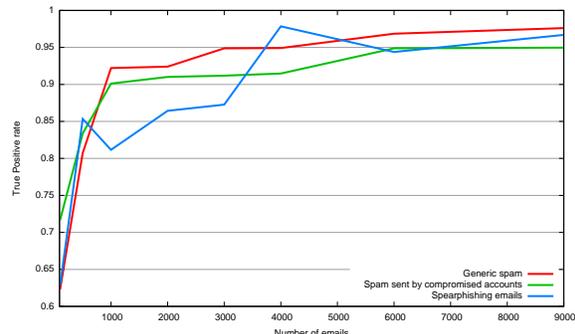


Figure 4: Analysis of the True Positive rate for our attack datasets. On the X axis we have the number of emails that a user sent in the past. As we can see, IDENTITYMAILER is able to block more and more emails as malicious as the sending history of a user increases.

\mathbf{S}_2 , and \mathbf{S}_3 , and each user U , we edited the **From:** field in the email to look like it was sent by U , and ran IDENTITYMAILER against it, to see whether the email would have been flagged as anomalous if it was being sent from U 's account. Since IDENTITYMAILER does not use, at least at this stage, some header fields such as the **X-Mailer** or sender IP address, no additional editing was required for our test purposes.

Figure 4 shows the detection results of IDENTITYMAILER on the three datasets. As for the validation of the classifier, the performance of IDENTITYMAILER depends on how many emails each user has sent in the past, as well as the consistency of a user's behavior while sending emails. In general, an email history of 200 messages is enough to reach a true positive rate of 80%, while sent email logs of 1,000 emails or more lead to 90% detection rate. As a peak, IDENTITYMAILER reaches 98% true positives for certain users. These detection numbers are actually very promising and demonstrate very good performance of the system. To put things into perspective, for the very same evaluation datasets \mathbf{S}_1 , \mathbf{S}_2 , and \mathbf{S}_3 , most state-of-the-art systems would entirely fail to detect any of these emails as malicious. Hence, being able to detect most of these particularly insidious spearphishing emails is undoubtedly a major

improvement over existing systems. In fact, IDENTITYMAILER can be seen as an additional protection layer that complements existing anti-spam systems, in order to block advanced spearphishing emails that other email protection layers would not be able to detect.

5.4 Fighting an Adapting Enemy

As we said previously, the techniques used in IDENTITYMAILER for building the email-sending behavioral profiles enable us to extract those characteristics that identify a certain user’s sending behavior best, hence performing accurate classification and obtaining better detection. Of course, an attacker could imitate a user’s sending behavior, as an attempt to evade detection by our system. An attacker who compromised a user’s machine or email account typically has access to the emails sent by that user in the past (for example, through the *Sent* folder of the user’s mailer program). He can thus leverage these emails to learn what are the most common characteristics in a users’ email-sending behavior, and replicate them in his malicious emails. However, since the attacker does not have access to all emails sent by all other users in the organization, it is difficult for him to know whether those characteristics, although common in the user’s behavior, distinguish the user well from the others. In fact, the most common characteristics of a user’s behavior might be shared with many other users, thus by replicating them an attacker would not obtain any effect on the success of his attack. Even worse, he might focus on characteristics that have a marginal importance or very low relevance in the behavioral profile built by IDENTITYMAILER, and make other characteristics stand out, in fact making detection easier.

To investigate what would be the effects of an attacker actively trying to evade our system, we developed a number of evasion techniques, and tested them on the spearphishing dataset S_3 . In particular, for each user U , and every email M in S_3 , we extracted the feature vector \mathbf{V}_m , and modified a number of parameters, to make the email look more similar to the ones typically sent by U . We then applied the same detection approach described in Section 5.3 to this

modified dataset. In the following, we describe the different evasion schemes that we developed.

Coworkers. This is the simplest evasion scheme. Instead of sending attack emails to email addresses outside the user’s organization, the attacker sends an email to another user within the same company, with whom the victim exchanged at least one email in the past. The destination address is picked at random.

High activity time period. In this evasion scheme, the attacker sends emails on the day and hour during which the user has sent the highest number of emails in the past.

Top contact. This technique is similar to the *coworkers* one, except that the destination address is chosen as the one to which the user sent the highest number of emails.

Mimic. In this technique, the attacker tries to replicate the writing style of the victim. In particular, he learns the n most common functional and context-specific words used by the user, and he uses them in the attack emails with the same ratio as typically used by the victim in her legitimate emails. We experimented two different evasion techniques of this kind, replicating the 10 and 20 most common words used by a user, respectively.

We tested these evasion techniques described here above individually, as well as in conjunction with each other. Table 3 provides a summary of the results for every (combination of) evasion techniques, compared with the results obtained with the unmodified dataset. In each evasion scenario, the *failure*, *success*, and *no effect* columns indicate the number of victim users for which the evasion attack has failed, was successful, or did not change, respectively. The *average change* field indicates the average percentage of emails that successfully evaded IDENTITYMAILER for that strategy, compared to the detection on the unmodified dataset. A negative value indicates that, on average, IDENTITYMAILER performed better on the modified dataset than on the original one.

As it can be seen, none of the evasion techniques guarantees that the attack emails will be more successful in evading IDENTITYMAILER. All evasion techniques (except for the *coworkers* and *top contact* ones) provide, on average, an increase in the number of emails that are not detected as malicious by

Type of Evasion	Failure	Success	No Effect	Avg. Change
C	5	0	143	-0.3%
T	81	63	4	+3.4%
T + C	6	0	142	-0.3%
M_10	87	49	12	+2.4%
M_20	91	50	7	+5.0%
T + TC	81	63	4	+3.4%
T + TC + M_10	73	73	2	+5.7%
T + TC + M_20	65	78	5	+8.4%

Table 3: Summary of the results for different evasion strategies: Coworkers (C), Time (T), Top contact (TC), Mimic 10 words (M_10), Mimic 20 words (M_20), and combinations of them. This table shows that evading IDENTITYMAILER’s detection is hard: even in the most successful case of evasion, the attack fails for 43% of the users.

our approach. However, even in the most successful case, in which we use the *time*, *top contact*, and *mimic 20* techniques in conjunction, the evasion fails for 43% of the users, allowing IDENTITYMAILER to detect more emails as malicious than for the unmodified dataset. If we look at the entire user population, this advanced evasion scheme would have enabled an additional 8.4% of emails to evade detection; this means that, for a user who sent 1,000 emails in the past, IDENTITYMAILER would have still been able to block 82% spearphishing emails on average. Given these results, we can conclude that it is not straightforward for an attacker to evade detection by IDENTITYMAILER, and that our system is quite resilient against this type of evasion technique even when the attacker tries to mimic the victim’s email sending habits.

An attacker might try a replay attack, by taking an email that was written by a user in the past, and sending it again. This strategy has the limitation that the attack is limited to the content that the user has already written in the past. We acknowledge that in some cases this strategy might be viable. However, this more extreme case of mimicry attack would be straightforward to mitigate, as we can easily trigger an identity verification process any time an email results in a feature vector that is identical to another one observed in the past.

Another technique that an attacker could try is

imitating the email-sending behavior learning phase of our system. To this end, he might leverage the emails that other users sent to the victim in the past as \mathbf{M}_o . The attacker can find these emails, for example, in the *Inbox* of the victim’s mailer program. In principle, this technique could help in making the attack more successful, and evade IDENTITYMAILER. However, the information that an attacker can learn from the emails received by a user in the past is limited. For example, it does not give any information on what the social networks of the other users in the company look like, and it only shows the behavior that third party showed when interacting with that specific user. An attacker might get additional knowledge of the company’s emails by compromising additional email accounts. If he obtained access to a significant number of accounts, he might be able to replicate the learning process of IDENTITYMAILER and evade our system. However, an attack of such breadth is hard to set up, and once an attacker gets such a pervasive presence in the company’s network, there is not much that our approach (or possibly any other) can do.

6 Discussion and limitations

Our results show that IDENTITYMAILER is successful in detecting and blocking attack emails that appear to have been written by a legitimate user, but

have actually been authored by an attacker abusing someone else’s account. Like most detection systems, however, IDENTITYMAILER has some limitations. The main limitation is that, to be effective, IDENTITYMAILER requires an email history of at least 1,000 emails. This makes it difficult to protect, for example, the new hires of a company. We argue that email is such a pervasive communication medium that it should not take long to obtain a sufficient number of emails even for a new employee. In addition, a new hire is probably not going to be a good target for an attacker, either due to a lack of visibility or because an attacker would prefer to target more influential people in the company. These individuals, however, will have a long email-sending history, and IDENTITYMAILER will thus protect them effectively. Another possible limitation in a corporate setting is that high-ranked executives might delegate their assistants to write some emails on their behalf. This practice might generate false positives, because IDENTITYMAILER would detect that those emails were not written by the owner of the account. A possible mitigation here is to learn multiple email-sending behaviors corresponding to a limited set of individuals who are using the same account, and thus avoid generating an alert if the email appears to be authored by any of those users.

Another limitation of IDENTITYMAILER is that writing-habit features are specific to the English language. If our approach had to protect the employees of a company whose main language is different than English, we would have to develop another set of language-specific features. Previous research showed that this is feasible even for Asian languages, which have very different characteristics than English [47].

In Section 5.4 we showed that it is difficult for attackers to successfully evade our system. However, attackers could exploit weak points in IDENTITYMAILER’s deployment at specific companies. For example, if an organization used a publicly-available set of emails as $\mathbf{M}_{u,x}$, an attacker might get access to that dataset, use it in a similar way to learn the models and thus evade our system. However, the attacker would still not have access to the emails used by all the other employees of the company, and the knowledge of the attacker would still be incomplete.

Similarly, an attacker might try to build emails that resemble the victim’s style, for example by using a Context Free Grammar (CFG). If the model used by the attacker is not complete, however, he will still not be guaranteed to succeed.

Another problem that we have to consider is the privacy of users. The email sending behavior is built not only by leveraging a user’s personal emails, but also by leveraging the ones sent by her coworkers. However, feature vectors built from the email are kept among the client and the server, and are never seen by the users. Also, the server has to only keep the feature vector relative to an email, instead of the email itself. Therefore, we argue that the privacy implications caused by IDENTITYMAILER are still acceptable.

Another concern is that some domains, such as large webmail providers, have a very diverse set of users, and thus it might be challenging to accurately model their behavior. We argue that the focus of IDENTITYMAILER is on corporate users, and we assume that their behavior is more consistent than the one of general-purpose email providers. In addition, large webmails have access to additional signals that are not included in our threat model (such as login patterns and IP addresses), which can also be leveraged to build a behavioral profile.

7 Related Work

Our approach protects the identity of users against attackers sending emails on their behalf. To this end, we borrow some ideas from anti-spam techniques, as well as from the field of forged text detection and authorship identification. In the following, we discuss how our approach is related to previous work, and elaborate on the novelty of our method.

Spam Filtering: Existing work on spam filtering can be distinguished in two main categories: *origin-analysis* and *content-analysis* techniques. Origin-analysis techniques try to determine whether emails are good or bad by looking at their origin. Examples of characteristics that are indicative of a malicious emails can be the IP address or autonomous system that the email is sent from, or the geo-

graphical distance between the sender and the recipient [12, 26, 34, 42]. Other origin-based techniques include *Sender Policy Framework* (SPF) [43] and *DomainKeys Identified Mail* (DKIM) [19]. These techniques try to determine whether an email is actually coming from the address it claims to come from, by looking at the sender IP, or at a signature in the email headers. Origin-based techniques are widely deployed, because they allow servers to discard spam emails as soon as the malicious end connects to the mail server, saving resources and time. In addition, they reach good coverage, because most spam is sent by hosts that are part of a botnet, and therefore have a low reputation [35]. However, in the scenario in which IDENTITYMAILER works, origin-based techniques are useless, because the only thing they can do is confirming that an email has been sent by a certain account, regardless if it is a compromised one or not.

Content-analysis techniques look at the words in the message itself to determine if it is spam or not. Proposed methods include Naïve Bayes, Support Vector Machines, or other machine learning algorithms [7, 22, 28, 29]. Other systems detect spam by looking at malicious URLs in the email [15, 45]. Content-analysis techniques work well in detecting spam, however are too computationally intensive to be applied to every email that a busy mail server receives [36]. In IDENTITYMAILER, we solve this problem by analyzing emails as they get sent. We claim that this analysis is feasible, because the amount of emails that a mail server sends is lower than the amount of emails that it receives. Another problem of traditional content-analysis techniques is that they look for words that are indicative of spam. In the presence of a targeted attack, there might be no such words, since an attack email will use a language that is similar to the one used in everyday business emails. This is why in IDENTITYMAILER we learn the typical sending behavior of a user and match it against the emails she sends.

A number of systems have been proposed to counter specific types of spam, such as phishing. Such systems either look at features in the attack emails that are indicative of phishing content [9], or at characteristics of the web page that the links in the email point to [46]. IDENTITYMAILER is more general,

since it can detect any type of attack emails that is sent by compromised accounts. In addition, existing phishing techniques fail in detecting those emails that rely on advanced social engineering tactics, instead of redirecting the user to a phony login page.

Another category of spam detection techniques looks at the way in which spammers use the TCP or SMTP protocol [16, 33]. These techniques work well in practice against most spam, but are focused on detecting hosts that belong to a botnet, and are therefore useless in detecting the type of attacks that IDENTITYMAILER is designed to prevent.

Email Forgery Detection: A large corpus of research has been performed on determining the authorship of written text. These techniques typically leverage stylometry and machine learning and return the most probable author among a set of candidates [2, 5, 6, 11, 13]. From our point of view, these approaches suffer from two major problems: the first one is that they typically need a set of possible authors, which in our case we do not have. The second problem is that email bodies are often times too short to reliably determine the author by just looking at stylometry [10]. Lin et al. proposed a system that looks at the writing style of an email, and is able to tell whether that email was written by an author or not [20]. This approach may solve the first problem, but does not solve the second one, in which we have emails that are too short to make a meaningful decision. To mitigate this problem, in IDENTITYMAILER we leverage many other features other than stylometry, such as the times at which a user sends emails, or her social network.

Khonji et al. presented ASCAI [17], a system that detects if an email author has likely been forged. ASCAI looks at the most common n-grams in a user's emails, and flag as anomalous emails that contain words that the user rarely uses. Unlike IDENTITYMAILER, ASCAI looks for any word, instead of focusing on writeprint features (such as functional words). For this reason, this system would fail in detecting spearphishing emails whose content is about the same topics that the user typically discusses, but that have been authored by a different person. IDENTITYMAILER, on the other hand, has been designed to detect this type of stealthy spearphishing emails,

and is therefore effective in blocking them.

Stolfo et al. presented the Email Mining Toolkit (EMT) [31, 32]. This tool mines email logs to find communities of users who frequently interact with each other. After learning the communities, the system flags as anomalous emails that are addressed to people outside them. Although EMT leverages an idea similar to IDENTITYMAILER’s interaction features, it is tailored at detecting large-scale threats, such as worms spreading through email. The fact that IDENTITYMAILER leverages other types of features allow our system to detect more subtle, one-of-a-kind attack emails.

Egele et al. proposed a system that learns the behavior of users on Online Social Networks (OSN) and flags anomalous messages as possible compromises [8]. Because of the high number of false positives, their system can only detect large-scale campaigns, by aggregating similar anomalous messages. As we have shown, IDENTITYMAILER is able to detect attacks that are composed of a single email, and which have not been seen before.

8 Conclusions

We presented IDENTITYMAILER, a system that protects the mailbox of corporate users by checking whether an email has been written by the legitimate owner of an email account. This work is the first step towards the protection of individuals and companies against advanced email attacks, such as spearphishing. IDENTITYMAILER is able to learn the typical sending behavior of the account’s owner and can subsequently check all emails sent from the account against this profile in order to block advanced spearphishing attacks sent from a compromised email account. By performing experiments on real world datasets, we also showed that IDENTITYMAILER can effectively block attacks that state-of-the-art protection systems are unable to detect, and that an attacker has no clear strategy to make his emails look legitimate in order to evade our detection system.

Acknowledgments

This work was supported by the Symantec Research Labs Graduate Fellowship for the year 2012. The authors would like to thank the people at Symantec, in particular Marc Dacier, David T. Lin, Dermot Harnett, Joe Krug, David Cawley, and Nick Johnston for their support and comments. We would also like to thank Adam Doupè and Ali Zand for reviewing an early version of this paper. Your comments were highly appreciated.

References

- [1] The Spamhaus Project. <http://www.spamhaus.org>.
- [2] A. Abbasi, H. Chen, and J. F. Nunamaker. Stylometric identification in electronic markets: Scalability and robustness. *Journal of Management Information Systems*, 2008.
- [3] S. Afroz, M. Brennan, and R. Greenstadt. Detecting hoaxes, frauds, and deception in writing style online. In *IEEE Symposium on Security and Privacy*, 2012.
- [4] F. Aloul, S. Zahidi, and W. El-Hajj. Two factor authentication using mobile phones. In *IEEE/ACS International Conference on Computer Systems and Applications*, 2009.
- [5] K. Calix, M. Connors, D. Levy, H. Manzar, G. McCabe, and S. Westcott. Stylometry for e-mail author identification and authentication. *Proceedings of CSIS Research Day, Pace University*, 2008.
- [6] M. W. Corney. Analysing E-mail Text Authorship for Forensic Purposes. 2003.
- [7] H. Drucker, D. Wu, and V. N. Vapnik. Support vector machines for spam categorization. In *IEEE transactions on neural networks*, 1999.
- [8] M. Egele, G. Stringhini, C. Kruegel, and G. Vigna. COMPA: Detecting Compromised Social Network Accounts. In *Symposium on Network and Distributed System Security (NDSS)*, 2013.
- [9] Fette, I. and Sadeh, N. and Tomasic, A. Learning to Detect Phishing Emails. 2007.
- [10] R. Forsyth and D. Holmes. Feature finding for text classification. In *Literary and Linguistic Computing*, 1996.

- [11] G. Frantzeskou, E. Stamatatos, S. Gritzalis, C. E. Chaski, and B. S. Howald. Identifying authorship by byte-level n-grams: The source code author profile (scap) method. *International Journal of Digital Evidence*, 2007.
- [12] S. Hao, N. A. Syed, N. Feamster, A. G. Gray, and S. Krasser. Detecting Spammers with SNARE: Spatio-temporal Network-level Automatic Reputation Engine. In *USENIX Security Symposium*, 2009.
- [13] F. Iqbal, R. Hadjidj, B. Fung, and M. Debbabi. A novel approach of mining write-prints for authorship attribution in e-mail forensics. *Digital Investigation*, 2008.
- [14] T. N. Jagatic, N. A. Johnson, M. Jakobsson, and F. Menczer. Social phishing. *Communications of the ACM*, 2007.
- [15] J. P. John, A. Moshchuk, S. D. Gribble, and A. Krishnamurthy. Studying Spamming Botnets Using Botlab. In *USENIX Symposium on Networked Systems Design and Implementation (NSDI)*, 2009.
- [16] G. Kakavelakis, R. Beverly, and Y. J. Auto-learning of SMTP TCP Transport-Layer Features for Spam and Abusive Message Detection. In *USENIX Large Installation System Administration Conference*, 2011.
- [17] M. Khonji, Y. Iraqi, and A. Jones. Mitigation of spear phishing attacks: A content-based authorship identification framework. In *Internet Technology and Secured Transactions (ICITST), 2011 International Conference for*, 2011.
- [18] B. Klimt and Y. Yang. Introducing the Enron Corpus. In *CEAS*, 2004.
- [19] B. Leiba. DomainKeys Identified Mail (DKIM): Using digital signatures for domain verification. In *CEAS*, 2007.
- [20] E. Lin, J. Aycock, and M. Mannan. Lightweight client-side methods for detecting email forgery. In *Workshop on Information Security Applications (WISA)*, 2012.
- [21] McAfee Inc. Global Energe Cyberattacks: “Night-Dragon”, 2011.
- [22] T. Meyer and B. Whateley. SpamBayes: Effective open-source, Bayesian based, email classification system. In *CEAS*, 2004.
- [23] A. Narayanan, H. Paskov, N. Z. Gong, J. Bethencourt, E. Stefanov, E. C. R. Shin, and D. Song. On the feasibility of internet-scale author identification. In *IEEE Symposium on Security and Privacy*, 2012.
- [24] B. Parmar. Protecting against spear-phishing. *Computer Fraud & Security*, 2012.
- [25] J. Platt et al. Sequential minimal optimization: A fast algorithm for training support vector machines. 1998.
- [26] A. Ramachandran, N. Feamster, and S. Vempala. Filtering Spam with Behavioral Blacklisting. In *ACM Conference on Computer and Communications Security (CCS)*, 2007.
- [27] M. B. S. Sinha and F. Jahanian. Improving Spam Blacklisting Through Dynamic Thresholding and Speculative Aggregation. In *Symposium on Network and Distributed System Security (NDSS)*, 2010.
- [28] M. Sahami, S. Dumais, D. Heckermann, and E. Horvitz. A Bayesian approach to filtering junk e-mail. *Learning for Text Categorization*, 1998.
- [29] D. Sculley and G. M. Wachman. Relaxed Online SVMs for Spam Filtering. In *ACM SIGIR Conference on Research and Development in Information Retrieval*, 2007.
- [30] Securelist. Android Trojan Found in Targeted Attack. http://www.securelist.com/en/blog/208194186/Android_Trojan_Found_in_Targeted_Attack, 2013.
- [31] S. J. Stolfo, S. Hershkop, C.-W. Hu, W.-J. Li, O. Nimeskern, and K. Wang. Behavior-based modeling and its application to email analysis. *ACM Transactions on Internet Technology (TOIT)*, 2006.
- [32] S. J. Stolfo, S. Hershkop, K. Wang, O. Nimeskern, and C.-W. Hu. Behavior profiling of email. In *Intelligence and Security Informatics*. 2003.
- [33] G. Stringhini, M. Egele, A. Zarras, T. Holz, C. Kruegel, and G. Vigna. B@BEL: Leveraging Email Delivery for Spam Mitigation. In *USENIX Security Symposium*, 2012.
- [34] G. Stringhini, T. Holz, B. Stone-Gross, C. Kruegel, and G. Vigna. BotMagnifier: Locating Spambots on the Internet. In *USENIX Security Symposium*, 2011.
- [35] Symantec Corp. Symantec intelligence report. http://www.symanteccloud.com/mlireport/SYMCINT_2013_01_January.pdf, 2013.
- [36] B. Taylor. Sender reputation in a large webmail service. In *CEAS*, 2006.

- [37] The Radicati Group. Email Statistics Report. <http://www.radicati.com/wp/wp-content/uploads/2011/05/Email-Statistics-Report-2011-2015-Executive-Summary.pdf>.
- [38] O. Thonnard, L. Bilge, G. O’Gorman, S. Kiernan, and M. Lee. Industrial espionage and targeted attacks: understanding the characteristics of an escalating threat. In *Symposium on Recent Advances in Intrusion Detection (RAID)*, 2012.
- [39] Threatpost. New Email Worm Turns Back the Clock on Virus Attacks. http://threatpost.com/en_us/blogs/new-email-worm-turns-back-clock-virus-attacks-090910, 2010.
- [40] Trend Micro Inc. Spear-Phishing Email: Most Favored APT Attack Bait, 2012.
- [41] F. Tweedie and R. Baayern. How variable may a constant be? Measures of lexical richness in perspective. *Computers and the humanities*, 1998.
- [42] S. Venkataraman, S. Sen, O. Spatscheck, P. Haffner, and D. Song. Exploiting Network Structure for Proactive Spam Mitigation. In *USENIX Security Symposium*, 2007.
- [43] M. Wong and W. Schlitt. RFC 4408: Sender Policy Framework (SPF) for Authorizing Use of Domains in E-Mail, Version 1. <http://tools.ietf.org/html/rfc4408>, 2006.
- [44] G. Yule. The statistical study of literary vocabulary. *Cambridge University Press*, 1944.
- [45] M. Zalewski. p0f v3. <http://lcamtuf.coredump.cx/p0f3/>, 2012.
- [46] Zhang, Y. and Hong, J.I. and Cranor, L.F. Cantina: a Content-based Approach to Detecting Phishing Web Sites. 2007.
- [47] R. Zheng, J. Li, H. Chen, and Z. Huang. A Framework for Authorship Identification of Online Messages: Writing-Style Features and Classification Techniques. *Journal of the American Society for Information Science and Technology*, 2005.