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About Me

- Industrial Engineer
- PhD in Machine Learning
- Passionate about open-source
- Scikit-Learn contributor
- Organizer of Data Science Meetups



Who I've worked with















Agenda

- Phishing URL Detection using Machine Learning
- Malicious Cert Detection using Deep Learning
- DeepPhish: Simulating Malicious Al
- Demo 😩



Typical Phishing Example



Your Account Will Be Locked Forever If You Do Not Provide Accurate Informations

CLICK HERE TO UNBLOCK YOUR ACCOUNT ACCESS

This is an automated message. Please do not reply to this Email, as your response will not be received.

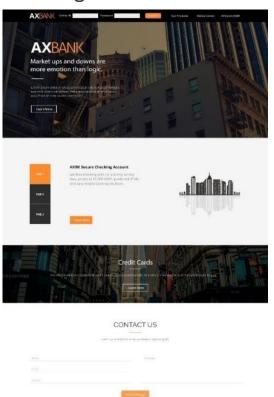


97% of cybercrimes and attacks start with a phishing email

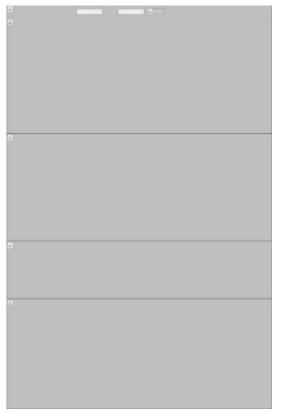


Why Phishing Detection is Hard?

Original Website



Only Using Images



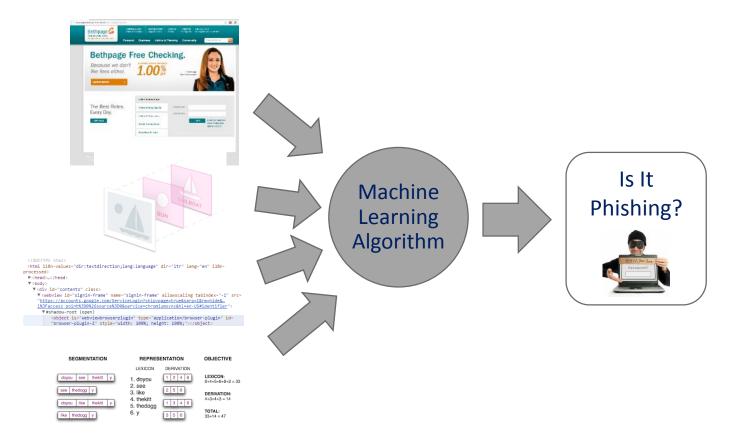
Subtle Changes







Ideal Phishing Detection System





Ideal Phishing Detection System

Issues with full content analysis:

- Time consuming
- Impractical to process millions of websites per day
- Hard to implement for small devices





There is always the need for an URL





Database of URLs

1,000,000 Phishing URLs from Phish Tank

http://moviesjingle.com/auto/163.com/index.php

 $http://\textbf{paypal.com}.update.account.\textbf{toughbook.cl}/8a30e847925afc5975161aeabe8930f\\ 1/?cmd=\\ home\\ \& dispatch=d09b78f5812945a73610edf38$

 $http://msystemtech.ru/components/com_users/Italy/zz/_Login.php?run=_login-submit\\\&session=68bbd43c854147324d77872062349924$

1,000,000 Legitimate URLs from Common Crawl

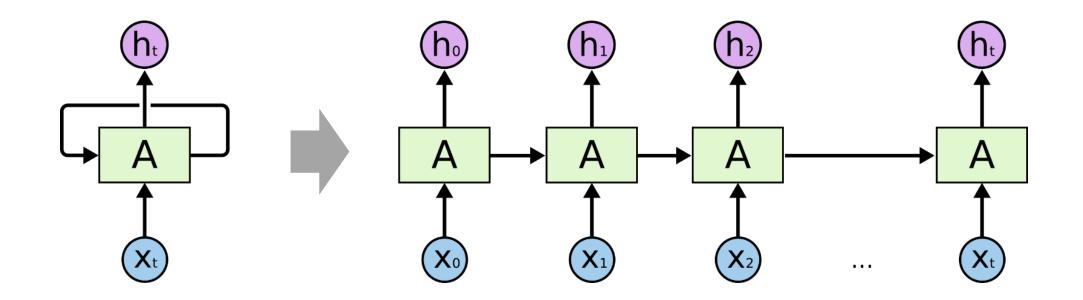
https://www.sanfordhealth.org/ChildrensHealth/Article/73980

 $http://www.grahamleader.com/ci_25029538/these-are-5-worst-super-bowl-halftime-shows\\ \& defid=1634182$

http://www.carolinaguesthouse.co.uk/onlinebooking/?industrytype=1\&startdate=201 3-09-05\&nights=2\&location\&productid=25d47a24-6b74

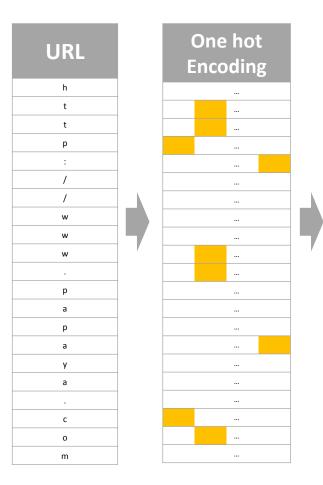


Recurrent Neural Networks RNN

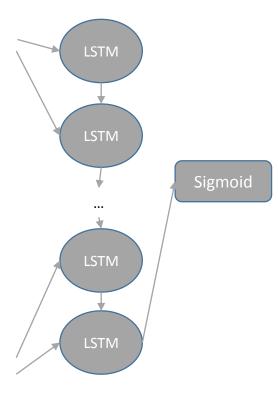




Recurrent Neural Networks RNN



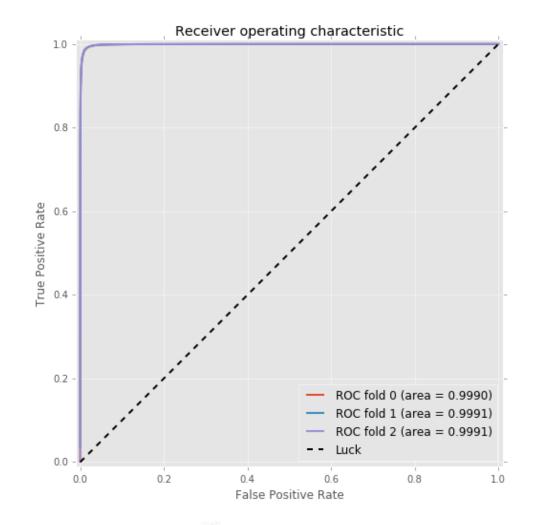
Er	nbe	ddiı	ng
3.2	1.2		1.7
6.4	2.3		2.6
6.4	3.0		1.7
3.4	2.6		3.4
2.6	3.8		2.6
3.5	3.2		6.4
1.7	4.2		6.4
8.6	2.4		6.4
4.3	2.9		6.4
2.2	3.4		3.4
3.2	2.6		2.6
4.2	2.2		3.5
2.4	3.2		1.7
2.9	1.7		8.6
3.0	6.4		2.6
2.6	6.4		3.8
3.8	3.4		3.2
3.3	2.6		2.2
3.1	2.2		2.9
1.8	3.2		3.0
2.5	6.4		2.6





URL Classification Results

3-Fold CV	Accuracy	Recall	Precision
Average	98.76%	98.93%	98.60%
Deviation	0.04%	0.02%	0.02%





URL Clas 93% PHS INCOME.

3-Fold CV

Average

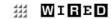
Deviation



##BHEU / @BLACK HAT EVENTS

Detecting Malicious URLs Is Not Enough!!





Phishing Schemes Are Using Encrypted Sites to Seem Legit

















LILY HAY NEWMAN SECURITY 12.05.17 02:32 PM ENCRYPTED SITES TO SEEM



3 GETTY IMAGES

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The Peculiar Math That Could Underlie the Laws of Nature

NATALIE WOLCHOVER



A Deadly Hunt for Hidden Treasure Spawns an Online Mystery

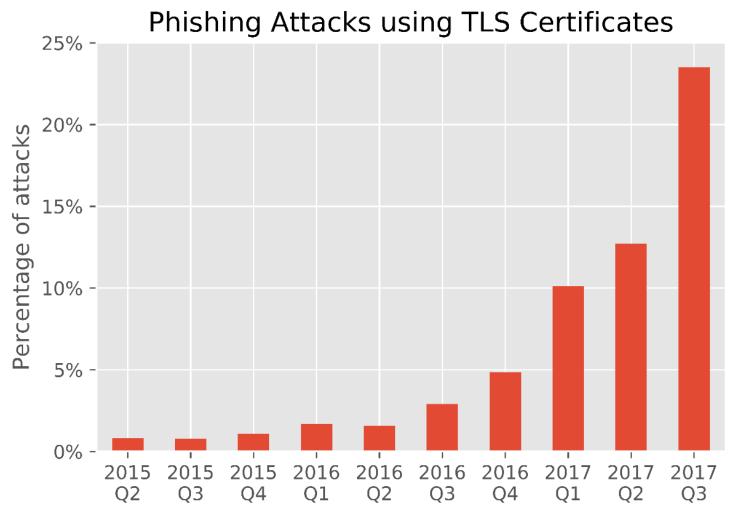
DAVID KUSHNER



CULTURE MoviePass Raises Prices, Limits First-Run Availability as Pressures...









What is a Web Certificate?









■ Secure | https://ultrabank.com





Forrester survey asked users: "Some websites receive the following browser user interface security indicator in the browser. What do you think the security indicator is intended to tell users?"

■ Secure | https://ultrabank.com

The website is safe: 82%

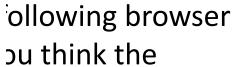
The website is encrypted: 75%

The website is trustworthy: 66%

The website is private: 32%







Forrester survey asked u user interface security ir security indicator is inter



5

The w

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Hunting Malicious TLS Certificates with Deep Neural Networks



Database of TLS Certificates

1,000,000 Legitimate Certificates from Common Crawl

CN = *.stackexchange.com, O = Stack Exchange, Inc., L = New York, S = NY, C = US

CN = slack.com, O = Slack Technologies, Inc., L = San Francisco, S = CA, C = US

CN = *.trello.com, O = Trello Inc., L = New York, S = New York, C = US

5,000 Phishing Certificates

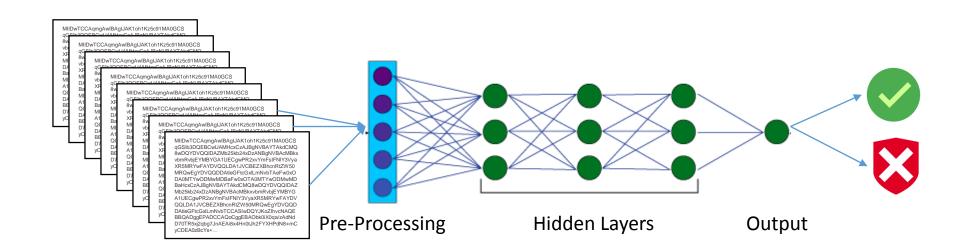
CN = localhost, L = Springfield

CN = localhost.localdomain

CN = example.com, L = Springfield

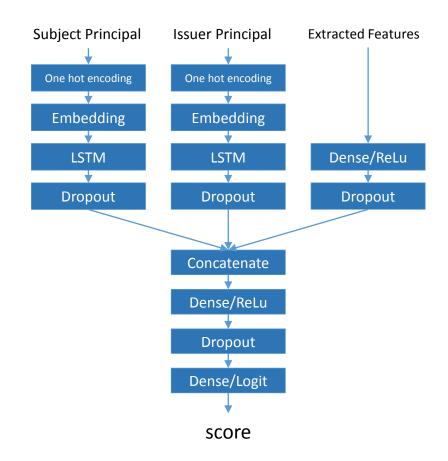


Deep Learning Algorithm





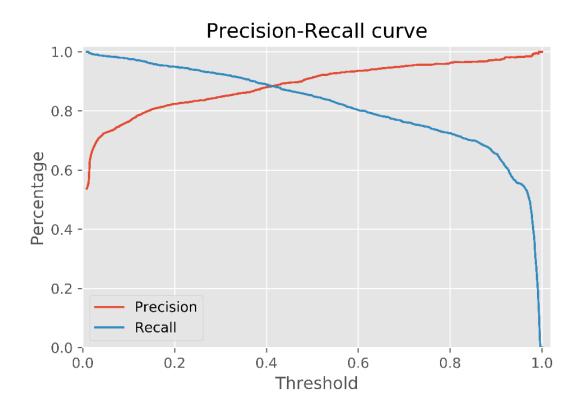
Deep Learning Algorithm





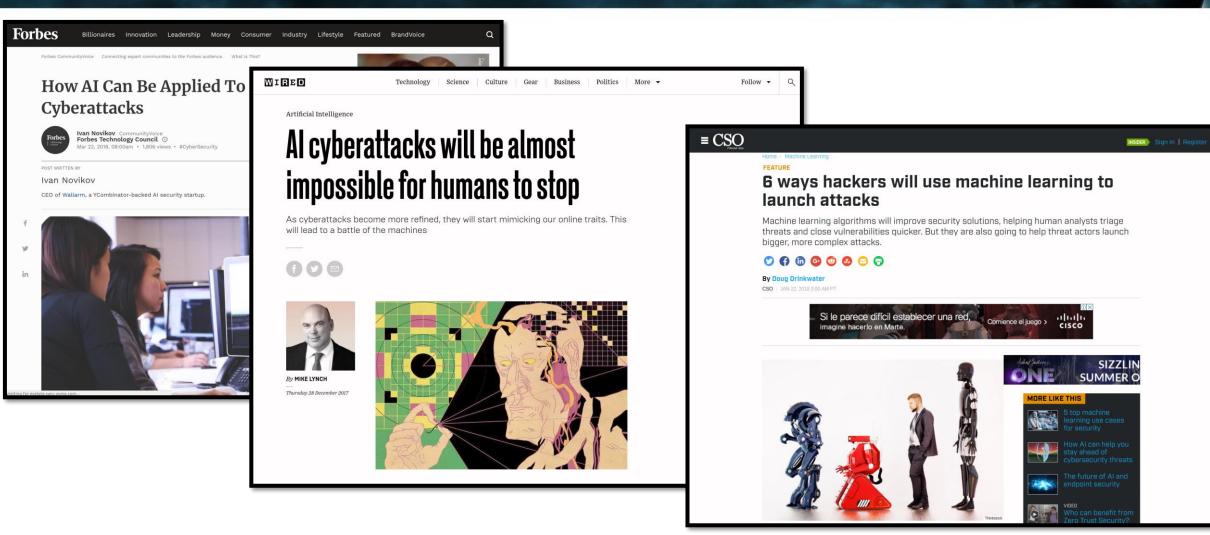
Malicious Cert Classification Results

5-Fold CV	Accuracy	Recall	Precision
Average	86.41%	83.20%	88.86%
Deviation	1.22%	3.29%	1.04%









DeepPhish Simulating Malicious Al

The Experiment:

Simulating Malicious Al

Identify individual threat actors

Run them through our own Al detection system

Improve their attacks using AI





Uncovering Threat Actors

 Objective: We want to understand effective patterns of each attacker to improve them through a AI model

 As we can not know attackers directly, we must learn from them through their attacks

 Database with 1.1M confirm phishing URLs collected from Phishtank



Threat Actor 1

naylorantiques.com



406 URLs

http://naylorantiques.com/components/com_contact/views/contact/tmpl/62

http://naylorantiques.com/docs/Auto/**Atendimento**/5BBROPI 6S3

http://naylorantiques.com/**Atualizacao Segura**/pictures/XG61YYMT_FXW0PWR8_5P2O7T2U_P9HND PQR/

http://naylorantiques.com/zifn3p72bsifn9hx9ldecd8jzl2f0xlwf

http://www.naylorantiques.com/JavaScript/charset=iso-8859-1/http-equiv/margin-bottom

Keywords

atendimento, jsf, identificacao, ponents, views, TV, mail, SHOW, COMPLETO, VILLA, MIX, ufi, pnref, story, tryy2ilr, Autentico

Check in database

106 domains

naylorantiques.com, netshelldemos.com, debbiebright.co.z, waldronfamilygppractice.co.uk , avea-vacances.com , psncodes2013.com uni5.net , 67.228.96.204, classificadosmaster.com.br, ibjjf.org

Visual Check



Visual Check

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Threat Actor 2

Vopus.org



13 URLs

http://www.vopus.org/es/images/cursos/thumbs/tdcanadatr ust

http://www.vopus.org/ru/media/tdcanadatrust/index.html

http://vopus.org/common/index.htm

http://www.vopus.org/es/images/cursos/thumbs/tdcanadatrust/index.html

http://vopus.org/descargas/otros/tdcanadatrust/index.html

Keywords

tdcanadatrust/index.html

Check in database

19 domains

friooptimo.com, kramerelementary.org, kalblue.com, vopus.org, artwood.co.kr, stephenpizzuti.com, heatherthinks.com, corvusseo.com, natikor.by, optioglobal.com, backfire.se, fncl.ma, greenant.de, mersintenisakademisi.com, cavtel.net

Visual Check



Visual Check

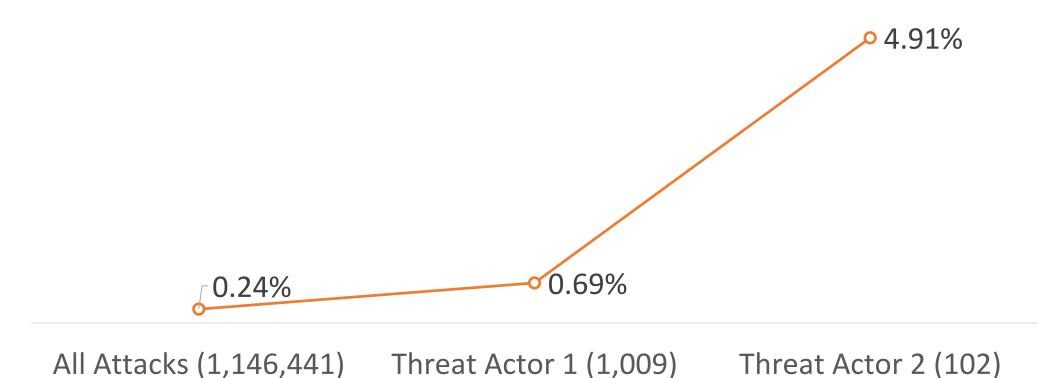
##BHEU / @BLACK HAT EVENTS

Simulating Malicious Al The Experiment: Improve their Identify Run them through individual attacks using our own Al threat actors detection system

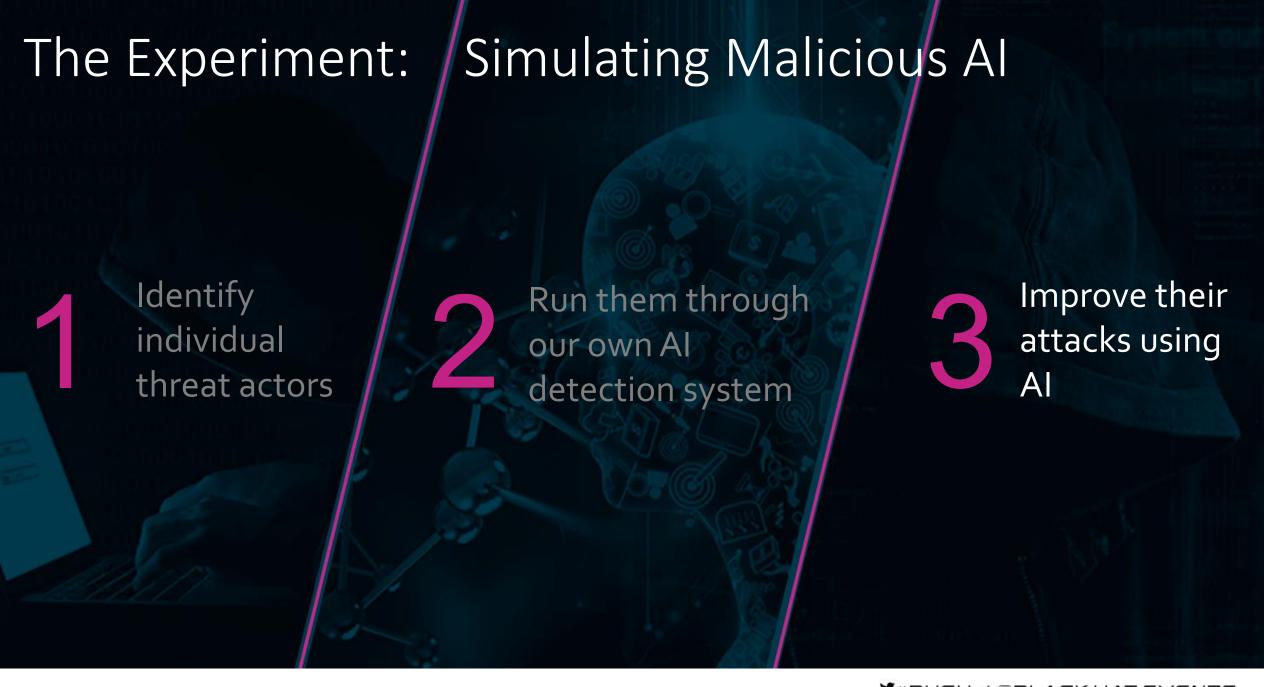




Threat Actors Effectiveness

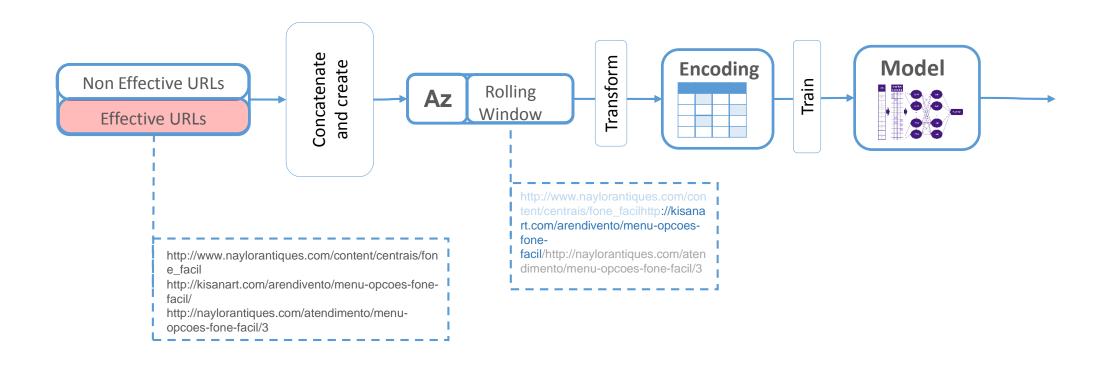


##BHEU / @BLACK HAT EVENTS



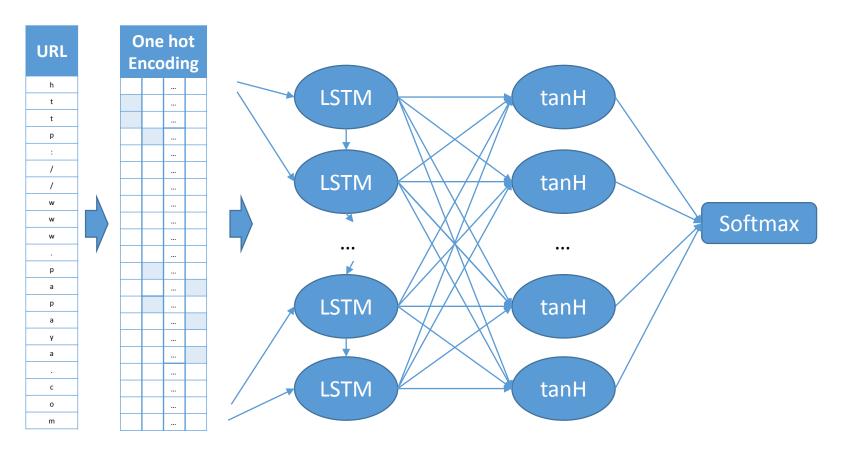


DeepPhish Algorithm - Training



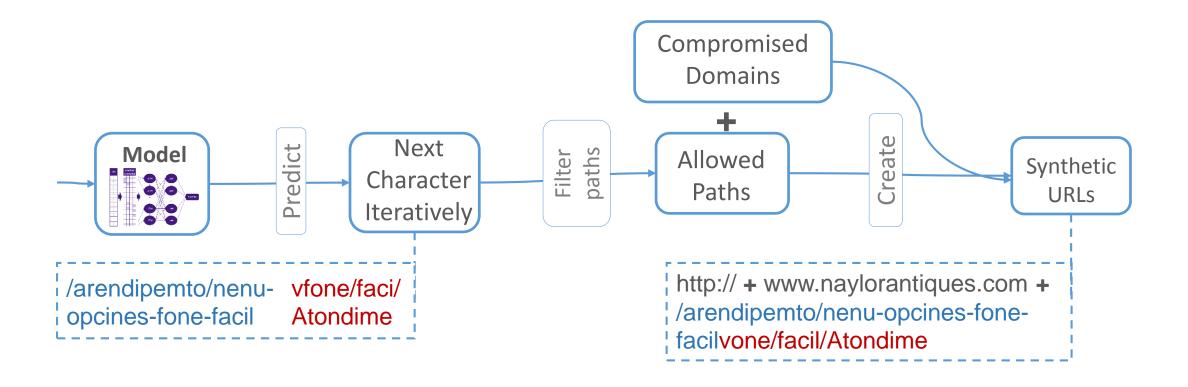


DeepPhish LSTM Network



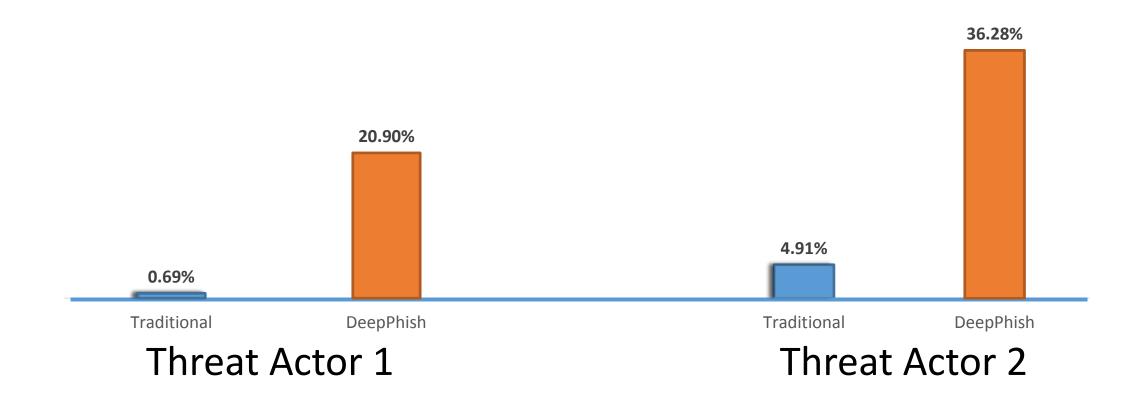


DeepPhish Algorithm - Prediction



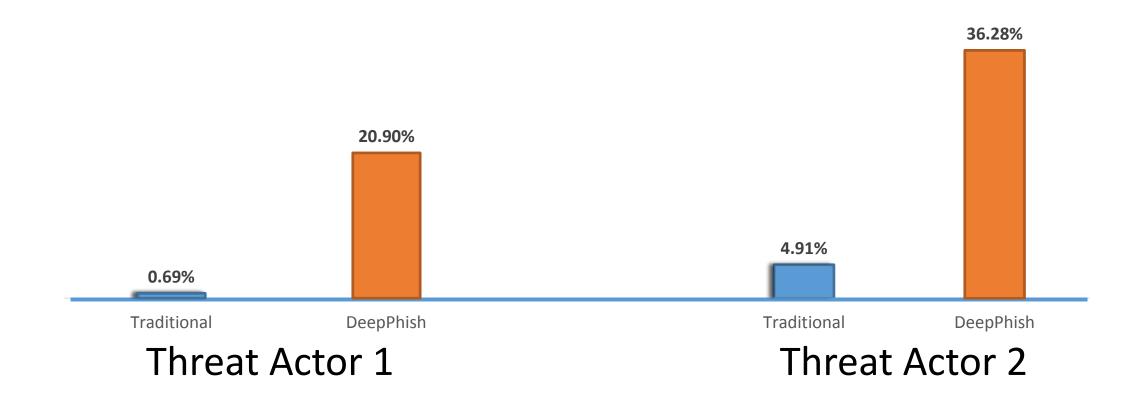


Traditional Attacks vs. Al-Driven Attacks





Traditional Attacks vs. Al-Driven Attacks





What's Next??







What's Next??

Al powered Attacks are real, as we probed with Deep Phish experiment.

We need to enhance our own AI detection systems to account for the possibility of attackers using AI.



DeepPhish: Simulating Malicious AI

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Abstract—In this work we describe how threat use AI algorithms to bypass AI phishing detection analyzed more than a million phishing URLs to und different strategies that threat actors use to create phis Assuming the role of an attacker, we simulate how diff actors may leverage Deep Neural Networks to en effectiveness rate. Using Long Short-Term Memory we created DeepPhish, an algorithm that learns to c phishing attacks. By training the DeepPhish algorit different threat actors, they were able to increase the ness from 0.69% to 20.9%, and 4.91% to 36.28%,

Keywords—Malicious AI; phishing detection; cybcurrent neural networks; long-short term memory net adversarial learning.

I. Introduction

Machine Learning (ML) and Artificial Intelli

Classifying Phishing URLs Using Recurrent

Alejandro Correa Bahnsen[†], Edu Javier Vargas [†]Easy *MindLab Research Group.

Email: acorrea@easysol.net, econtrerasb@unal.edu.co,

Abstract—As the technical skills and costs associated the deployment of phishing attacks decrease, we are witne an unprecedented level of scams that push the need for I methods to proactively detect phishing threats. In this we explored the use of URLs as input for machine lea models applied for phishing site prediction. In this way compared a feature-engineering approach followed by a rai forest classifier against a novel method based on recurrent n networks. We determined that the recurrent neural net approach provides an accuracy rate of 98.7% even without need of manual feature creation, beating by 5% the random method. This means it is a scalable and fast-acting prodetection system that does not require full content analysis

Keywords—Phishing detection; Cybercrime; Feature engiing; Recurrent neural networks; Long short term memory netw

I INTRODUCTION

Hunting Malicious TLS Certificates with Deep Neural Networks

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ABSTRACT

Encryption is widely used across the internet to secure communications and ensure that information cannot be intercepted and read by a third party. However, encryption also allows cybercriminals to hide their messages and carry out successful malware attacks while avoiding detection. Further aiding criminals is the fact that web browsers display a green lock symbol in the URL bar when a connection to a website is encrypted. This symbol gives a false sense of security to users, who are in turn more likely to fall victim to phishing attacks. The risk of encrypted traffic means that information security researchers must explore new techniques to detect, classify, and take countermeasures against malicious traffic. So far there exists no approach for TLS detection in the wild. In this paper, we propose a method for identifying malicious use of web certificates using deep neural networks. Our system uses the content of TLS certificates to successfully identify legitimate certificates as well as malicious patterns used by attackers. The results show that our system is capable of identifying malware certificates with an accuracy of 94.87% and phishing certificates with an accuracy of 88.64%.

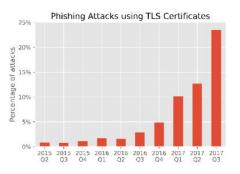


Figure 1: Evolution of phishing attacks using TLS [16].

■ Secure https://ultrabank.com



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