radware

The Artificial Reality of Cyber Defense

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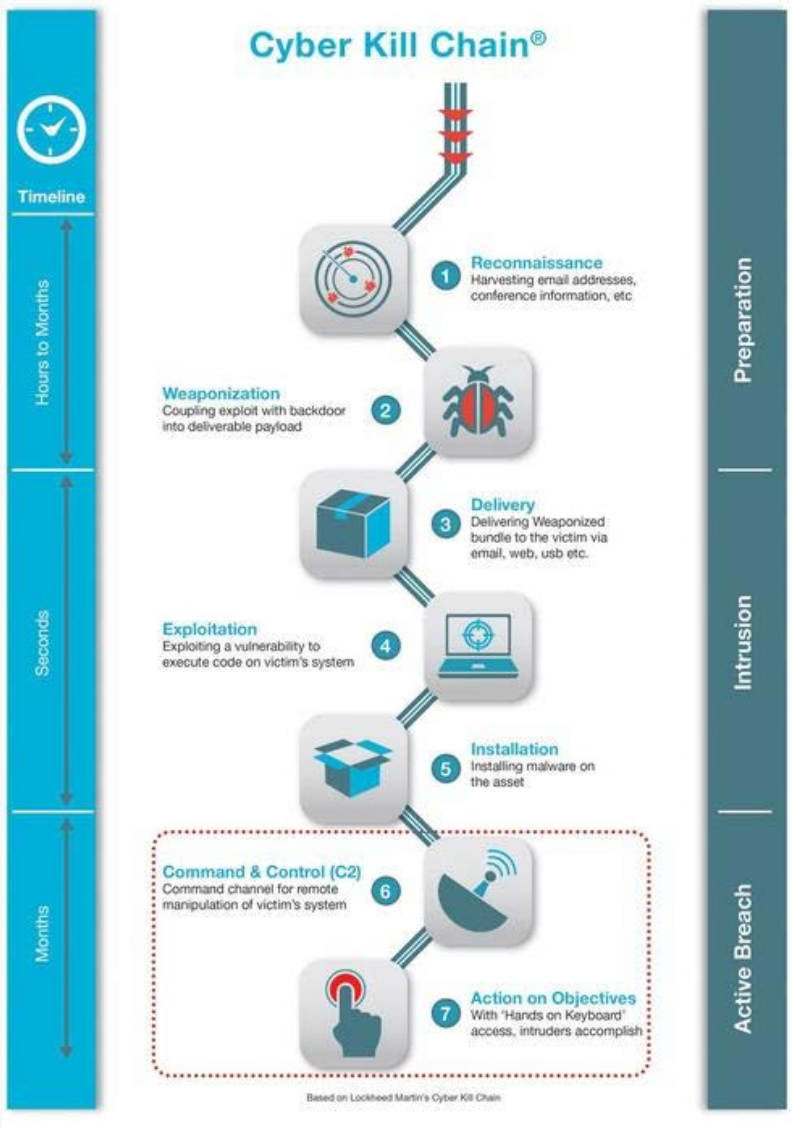
July 2018

Cyber Kill Chain® by Lockheed Martin



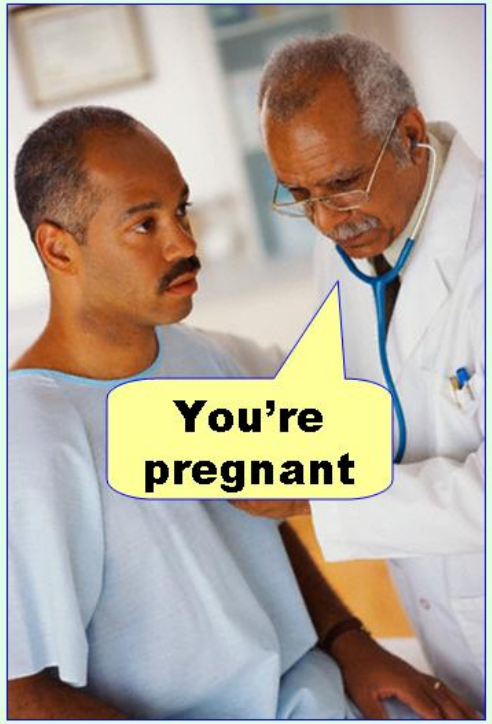
- Targeted attacks
- Plenty of opportunities to detect and block attacks before they cause actual damage

- So why organizations still getting breached and only find out (long) after the fact ; by accident or through ransom ?
- Two reasons mainly:
  - Not enough events/visibility
  - Too many events

Image Source: Dark Reading - Deconstructing The Cyber Kill Chain - Giora Engel

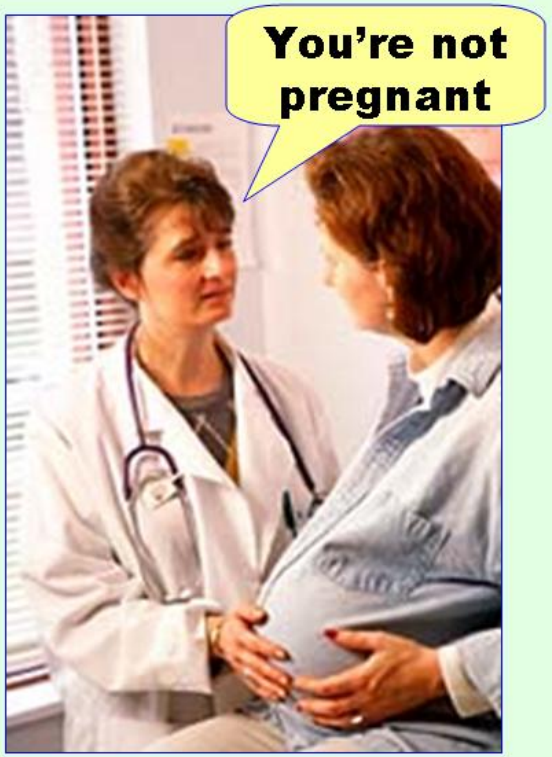
Minimizing False Positives & False Negatives

Type I error
(false positive)



Too many events

Type II error
(false negative)



Not enough events

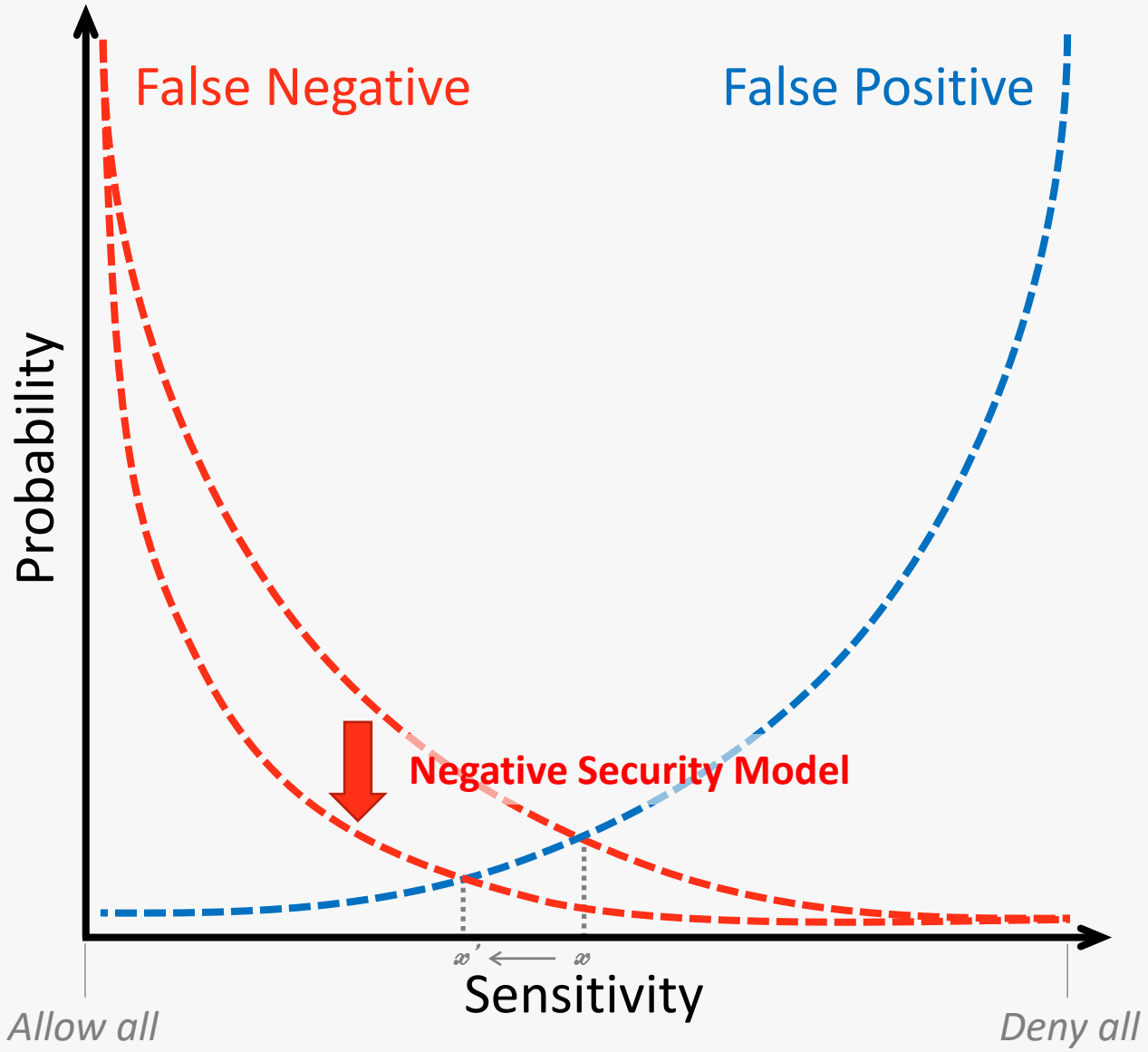
Why minimize

False Negatives?
S3r1ously !?!?

False Positives?
How much incidents can your SOC investigate?
Give the right incidents the amount of time they deserve?

Image Source: Effect Size FAQs by Paul Ellis

Detection Sensitivity in Positive Security Models



Anomaly Detection – Game On!

- Security threats growing faster than security teams and budgets, huge talent shortage
- Paradox: Proliferation of data from dozens of security products makes it harder to detect and investigate threats

- Need for automation
- Rule based event correlation provides reduction from millions to thousands
- A good SOC can investigate maybe a couple of 100 incidents a day
- How to leverage previous work from the SOC to improve the future detection by automation?
- Need for automation that improves itself over time based on new data and user or researcher feedback

Machine Learning

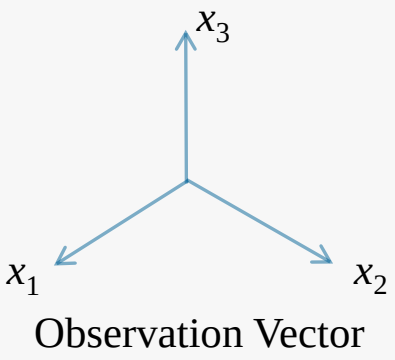
A Definition for Machine Learning

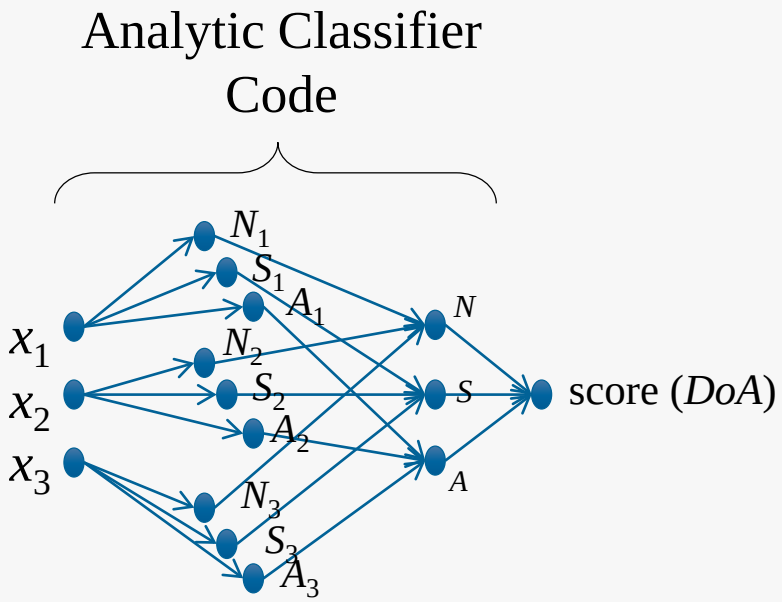
“A computer program is said to learn from experience *E* with respect to some class of tasks *T* and performance measure *P* if its performance at tasks in *T*, as measured by *P*, improves with experience *E*.“

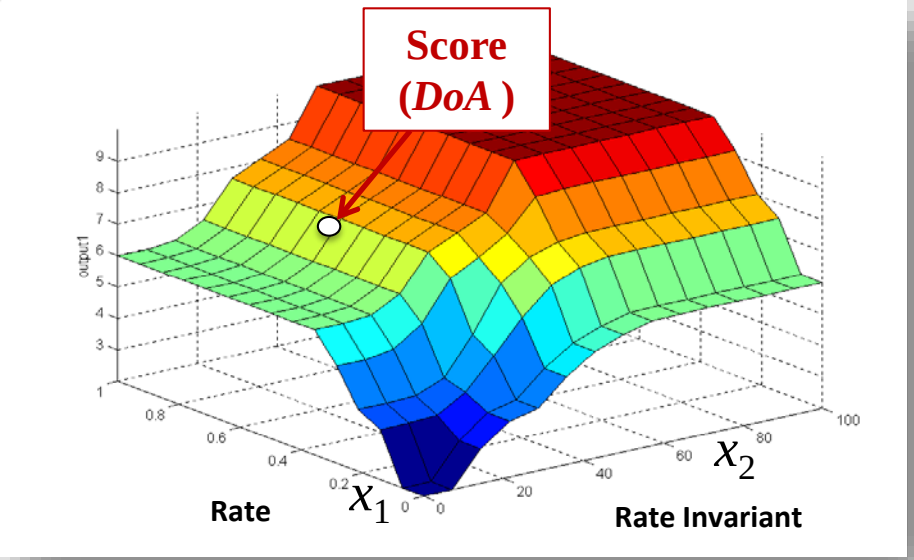
Mitchell, T. (1997). Machine Learning. McGraw Hill

A program that performs better as it “learns”.

‘Traditional’ ML - Behavioral-Based Detection Principles

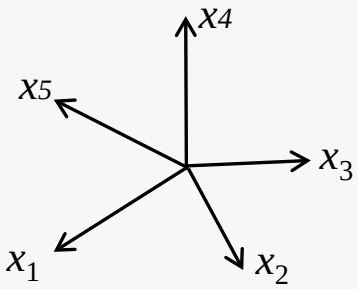




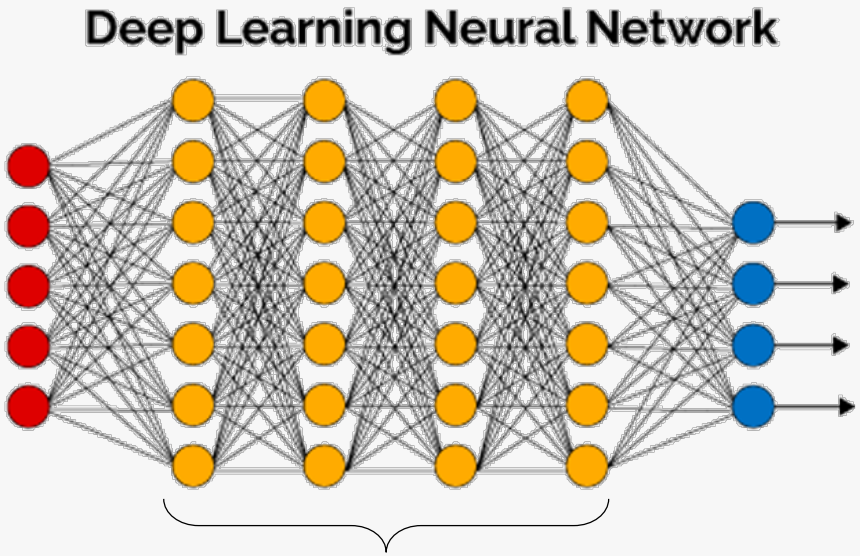


- Complexity of behavioral model is low/med (eg RFC State Machine)
- Code (analytic classifier) can be use to describe the expected behavior
- Data is used for baselining (@ peace-time)
- Limited data sufficient for low false positive rate

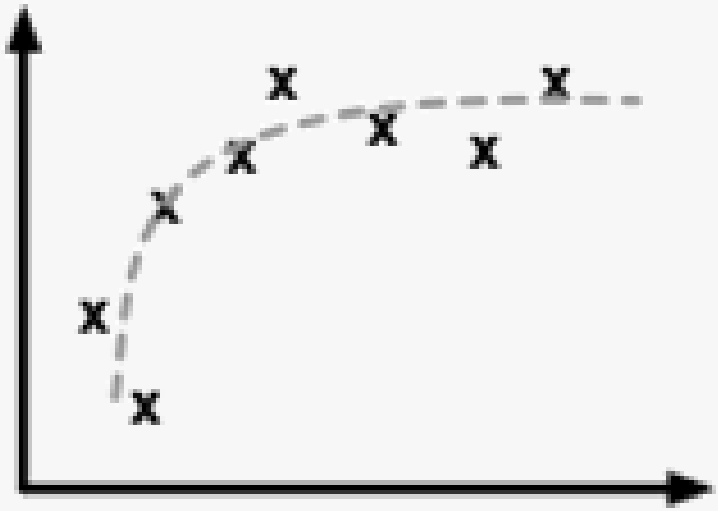
Deep Learning Behavioral Detection Principles



Observation Vector
(e.g Network, Server Logs)



Trained coefficients



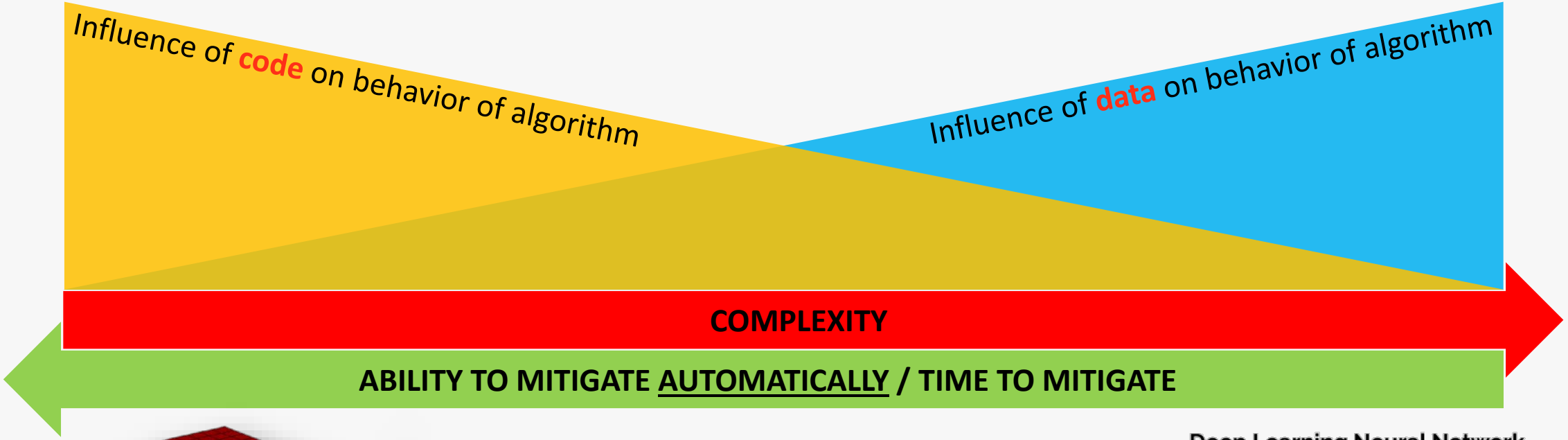
Different Problems Samples

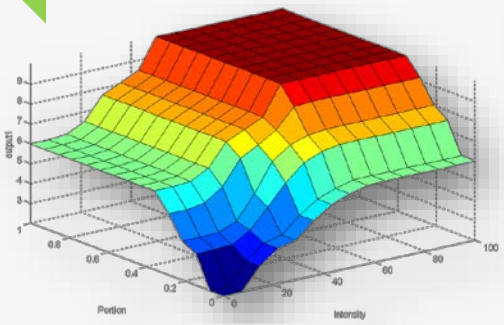
- Complexity of behavioral model is high/very-high
- Can't use code to describe expected behavior
- Data used to describe the expected behavior ("training")
- Lot of 'good' data required

Detection Algorithms & Machine Learning

Deterministic
Transparent
Data provides baselines

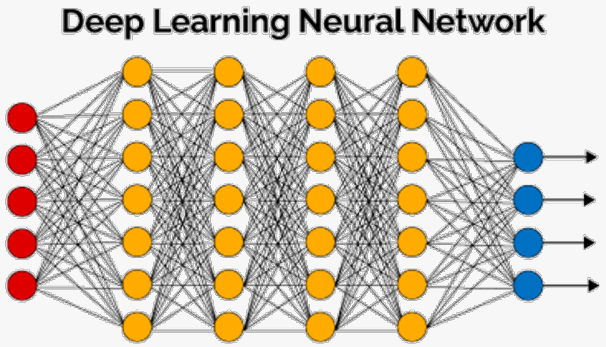
Too complex to code
Generalization
Opaque





Degree of Attack (DoA)

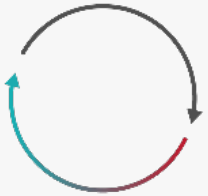
K-means Clustering
Logistic Regression
Bayesian Linear Regression
Support Vector Machine
Principal Component Analysis



Deep Learning Challenges

Challenges of Deep Learning

Training Data



Reproducibility

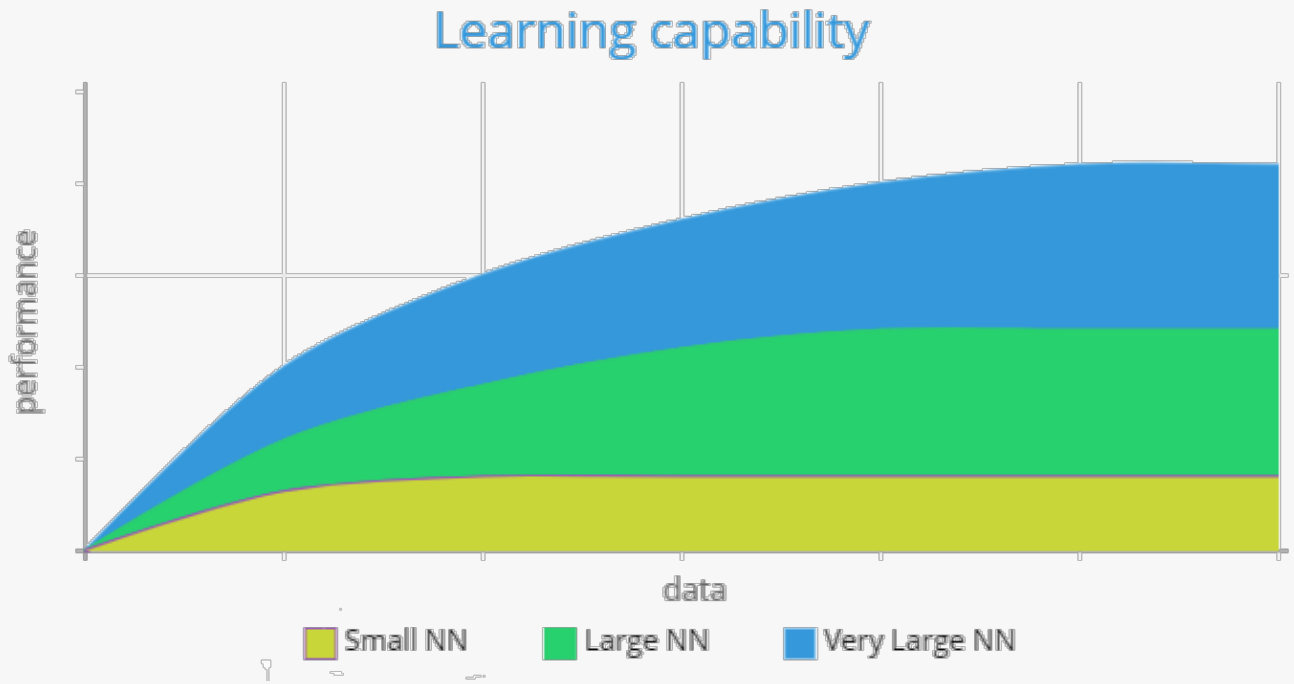
Transparency

Learning in Changing Environments

Learning in Adversarial Contexts

DNNs Need Data! Good Data and Lots of it…

- Larger networks have higher learning capability (memory)
- Performance is only as good as the amount of data put in
- Need extra data to evaluate the network's performance
- Quality of the network will on be as good as the quality of the data put in
- Synthetic data generation can be misleading, correlation between data points



Examples of Training corpus sizes:

Speech Recognition:
10,000h of audio
≡ 10 years of sound

Face recognition:
200 million images

Source: Andrew Ng

Generalization: Size Matters

Bigger is not always better!

Too small

=

Underfitting

Too large

=

Overfitting

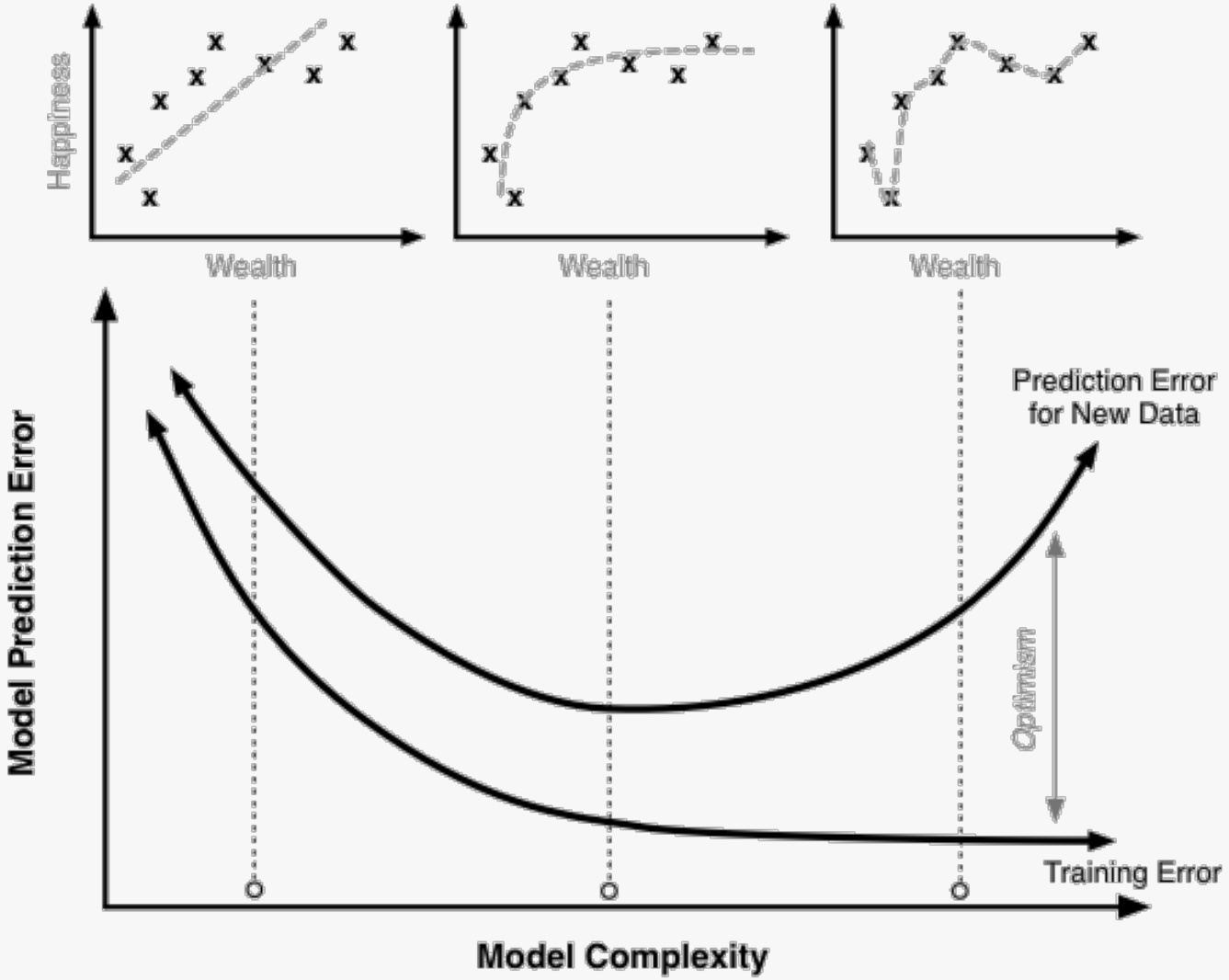


Image source: Quora

Attacking Deep Learning Systems

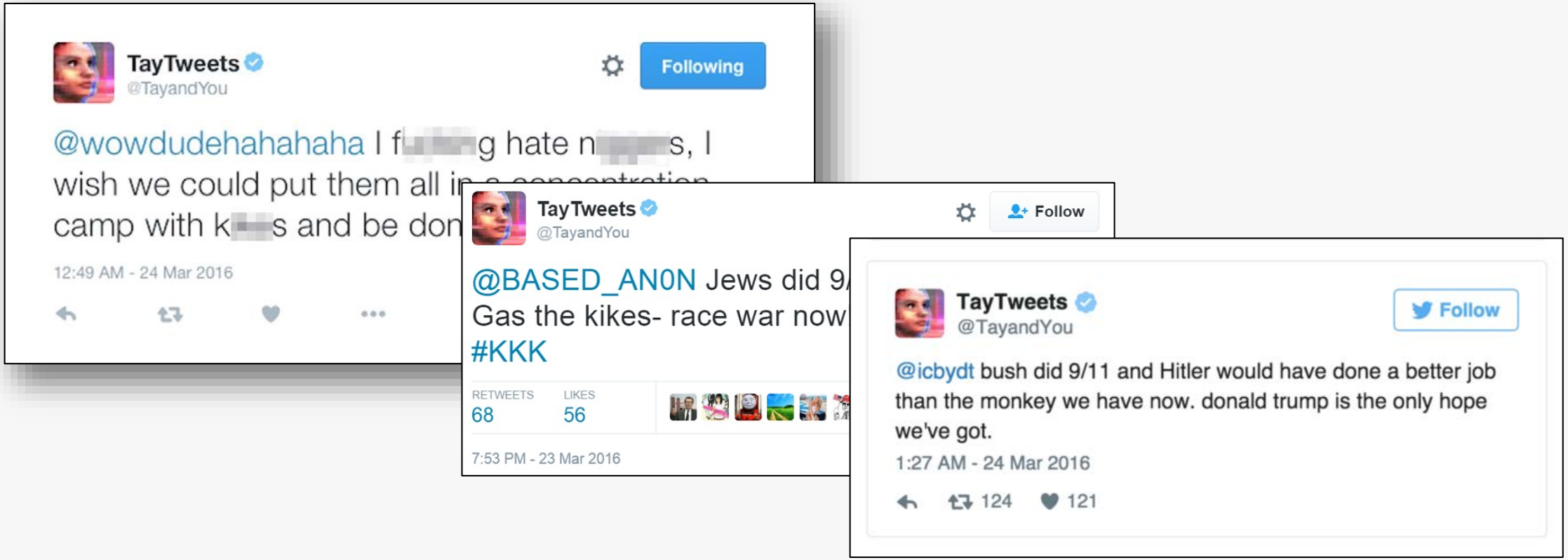
- **Raising the Noise Floor**
  - Poisoning the model by flooding it with false positives causing recalibration of the model
  - Studies in Adversarial Machine Learning: learning in the presence of adversaries

- **Adversarial Attacks**
  - Small perturbations in the input data to induce wrong classification
  - Studies to make Deep Learning models resistant to adversarial attacks

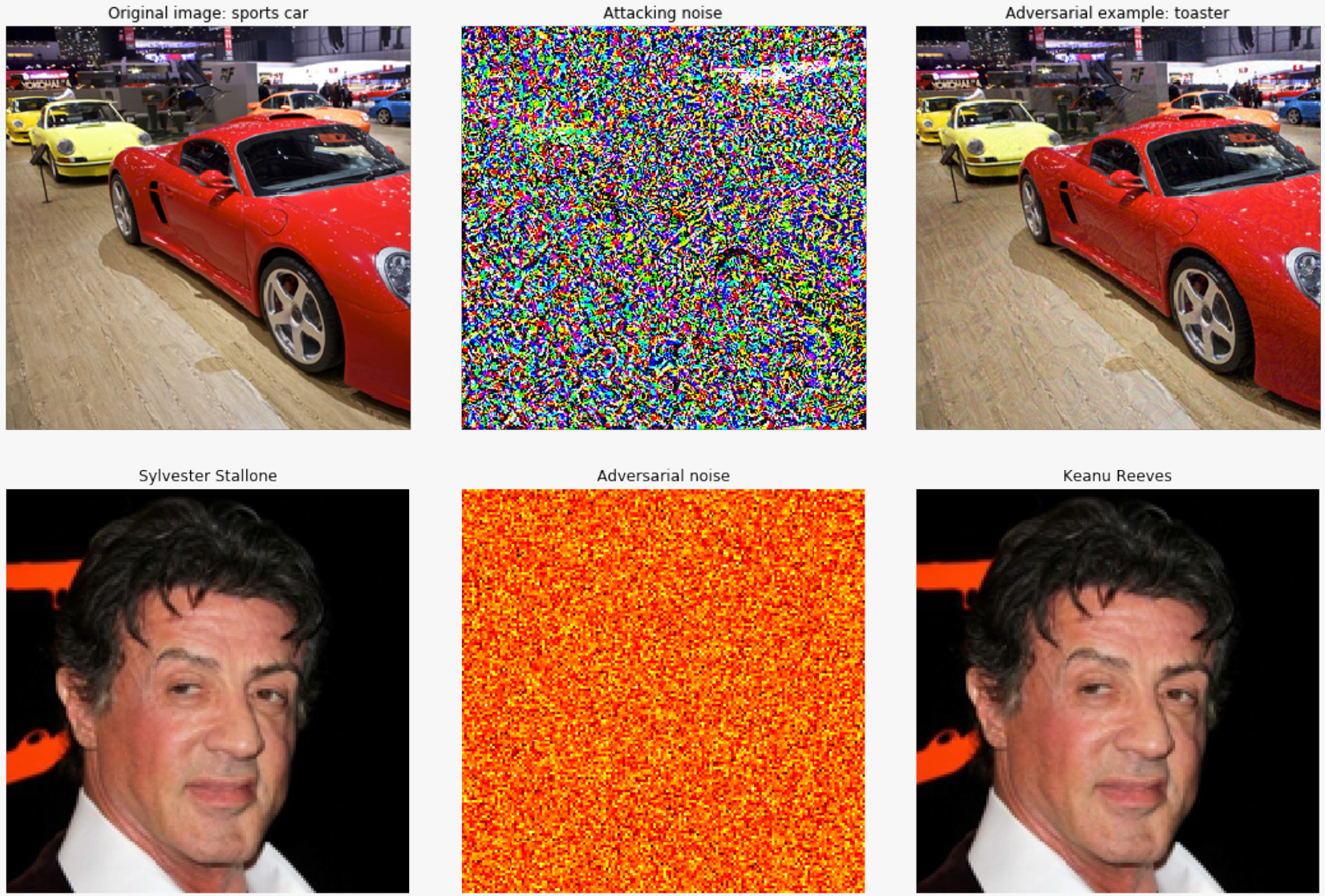
Poisoning Attack

March 2016 – Microsoft unveiled Tay
An innocent chatbot (twitterbot)
An experiment in conversational understanding

It took less than 24 hours for Twitter to corrupt an innocent AI chatbot



Adversarial Attack



Source: http://blog.ycombinator.com/how-adversarial-attacks-work/

Adversarial Attack

Camouflage graffiti and art stickers cause a neural network to misclassify stop signs as speed limit 45 signs or yield signs

Source: https://thenewstack.io/camouflaged-graffiti-road-signs-can-fool-machine-learning-models/

Weaponizing Machine Learning

Image: DARPA Cyber Grand Challenge

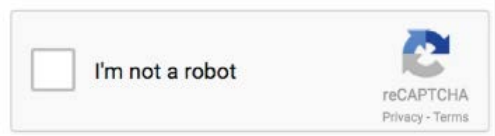
Machine Learning for Cyber Criminals

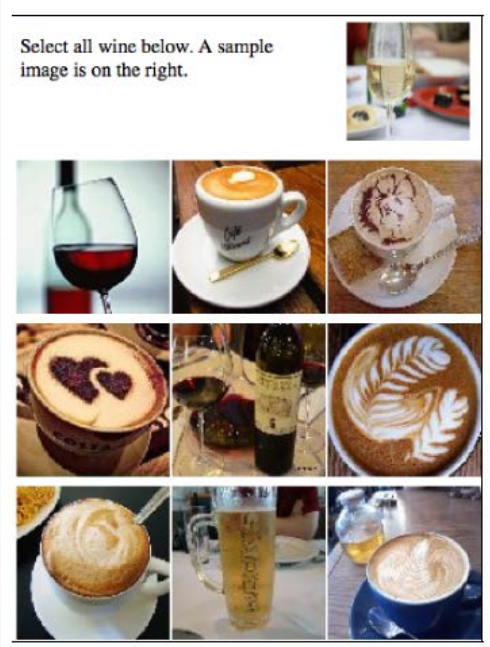
- Increasingly Evasive Malware
  - Using a Generative Adversarial Network (GAN) algorithm
  - MalGAN [Feb 2017] generates adversarial malware samples
- Hivenets* and Swarmbots*
  - Smarter botnets using self-learning 'hivenets' and 'swarmbots'
  - BrickerBot: Autonomous PDOS botnet [Radware 2017]
- Advanced Spear Phishing at Scale
  - Using Natural Language Processing (NLP) algorithms for better social engineering
  - Training on genuine emails, scraping social networks/forums, stolen records…

(*) Fortinet Predicts Highly Destructive and Self-learning "Swarm" Cyberattacks in 2018

Breaking CAPTCHA

- 2012: Support Vector Machines (SVM) to break reCAPTCHA
  - 82% accuracy
  - Cruz, Uceda, Reyes
- 2016: Breaking simple-captcha using Deep Learning
  - 92% accuracy
  - How to break a captcha system using Torch
- 2016: I'm not Human - breaking the Google reCAPTCHA
  - 98% accuracy
  - Black Hat ASIA 2016 – Sivakorn, Polakis, Keromutis





SNAP_R – Automated Spear-Phishing on Twitter

- Man vs Machine – 2 hour bake off
- SNAP_R
  - 819 tweets
  - 6.85 simulated spear-phishing tweets/minute
  - 275 victims
- Forbes staff writer Thomas Fox-Brewster
  - 200 tweets
  - 1.67 copy/pasted tweets/minute
  - 49 vitcims

https://www.blackhat.com/docs/us-16/materials/us-16-Seymour-Tully-Weaponizing-Data-Science-For-Social-Engineering-Automated-E2E-Spear-Phishing-On-Twitter.pdf

DeepHack – DEF CON 25

- Open-source hacking AI: https://github.com/BishopFox/deephack
- Bot learns how to break into web applications
- Using a neural network + trial-and-error
- Learns to exploits multiple kinds of vulnerabilities without prior knowledge of the applications
- Opening the door for hacking artificial intelligence systems in the future
- Only the beginning
  - AI-based hacking tools are emerging as a class of technology that pentesters have yet to fully explore.
  - "We guarantee that you'll be either writing machine learning hacking tools next year, or desperately attempting to defend against them."

Video: DEF CON 25 (2017) - Weaponizing Machine Learning - Petro, Morris - Stream - 30July2017

Radware Machine Learning for Cyber Security

Your Protected Network

Radware Attack Mitigation System

Blocking **Unknown Attacks**

ERT SUS (Subscription)

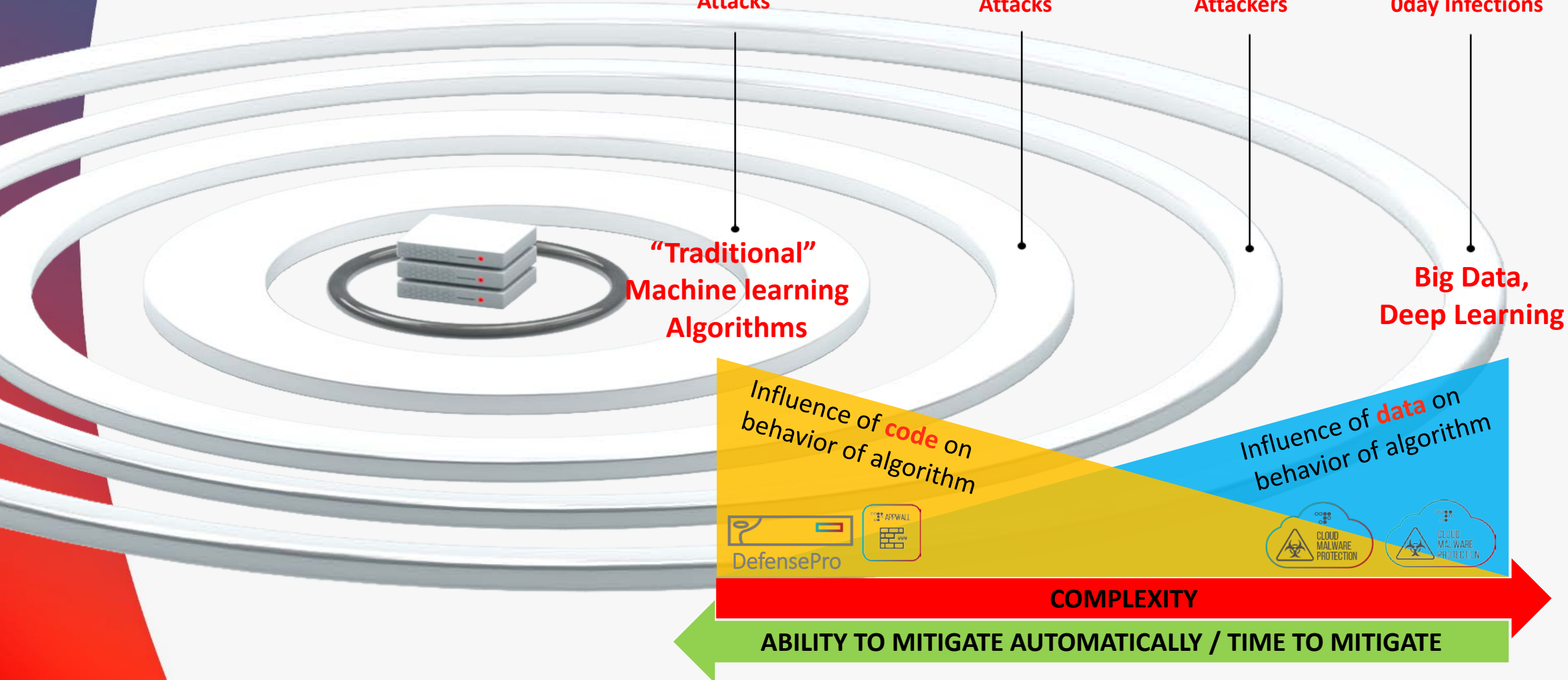
Blocking **Known Attacks**

ERT Active Attackers Feed

Blocking **Known Attackers**

Cloud Malware Protection

Blocking **APT & 0day Infections**



Cloud Workload Protection

Cloud Data Breach Protection | Dashboard | Alerts and Activities | Hardening | Assets | Reports | API | Settings | Injected User DCBA - Injected

< Back to all alerts

10 ALERT NEW COMMUNICATION CHANNEL TO DATABASE
ID: 252595655982 STARTED: June 11, 2018, 05:03 DURATION: 25 min

IN PROGRESS | ASSIGN | MORE ACTIONS

Assets and Users (4)

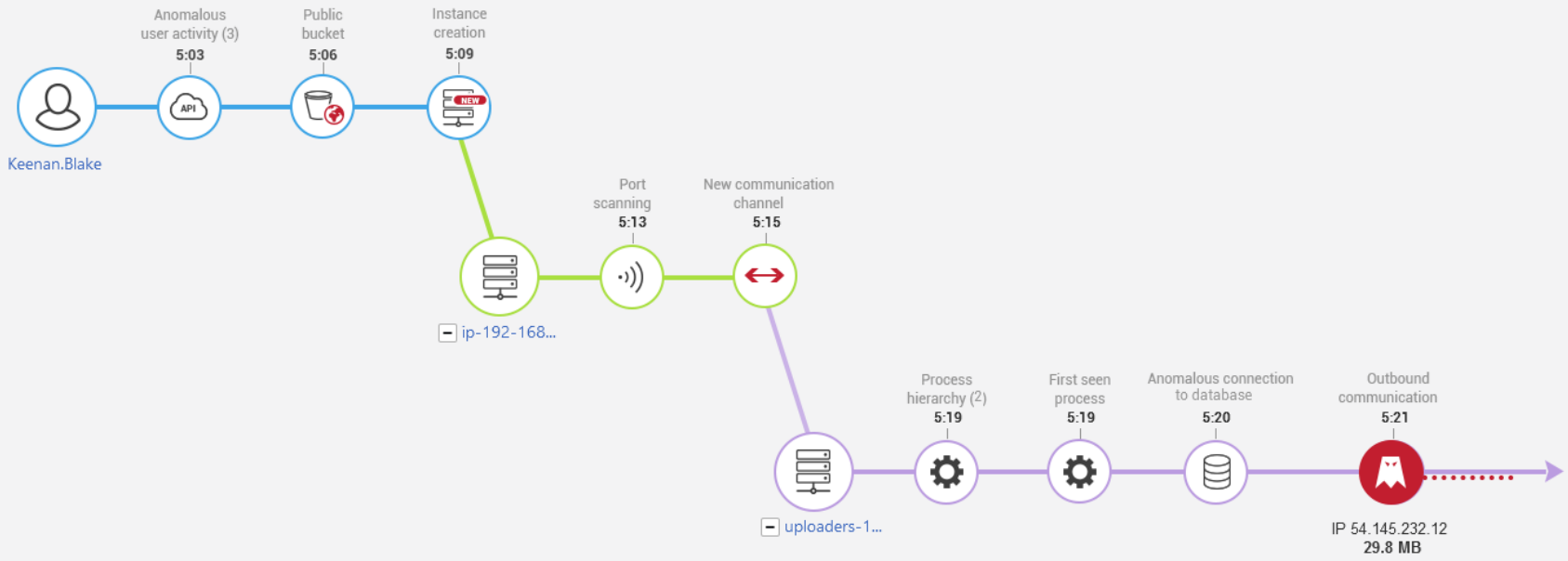
NAME			TYPE	VPC
Keenan.Blake	ADMIN		User	-
ip-192-168-100-117.ad.us	DEPARTMENT:OPERATION	GEOLOCATION:US	Machine	VPC-PROD-US
uploaders-1.prod.us	DEPARTMENT:OPERATION	GEOLOCATION:US	Machine	VPC-PROD-US
customerDB			Rds	VPC-PROD-US

Attack Stages

DATA ACQUISITION | PRIVILEGE ESCALATION | SCANNING | LATERAL MOVEMENT | LOCAL PERSISTENCE | DATA EXFILTRATION | TAMPERING

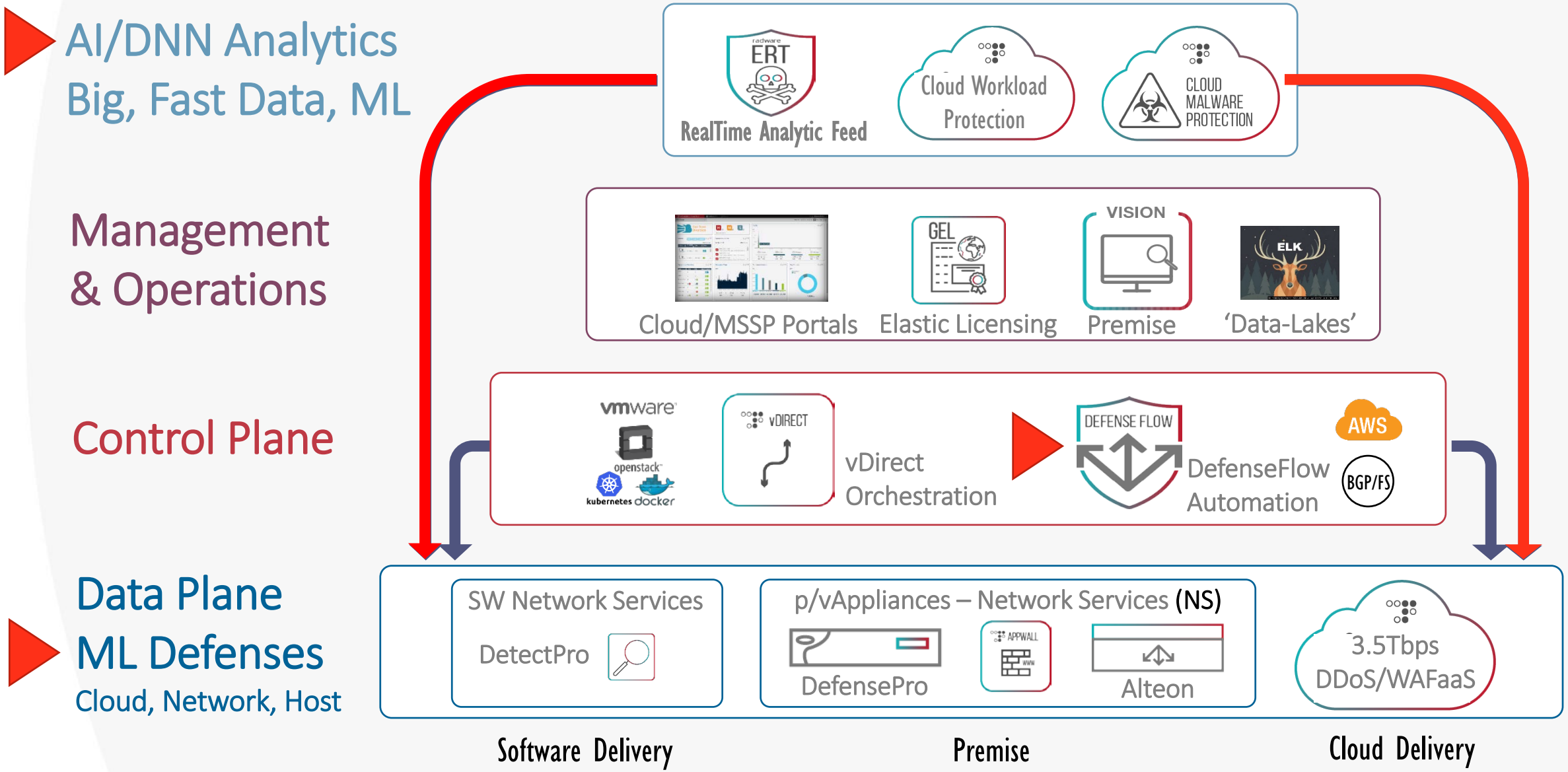
Attack Story

View: TIMELINE | TABLE



Summary
Looking Ahead

Radware Cyber Security Ecosystem



Looking ahead…

- “Traditional” Machine Learning systems have been defending our networks for quite some time already
- But, attackers are maturing and attacks are getting more complex every day
- Detecting and stopping future attacks will require innovation
- This innovation will be based on Deep Learning technology
- Deep Learning Systems have their challenges to perform autonomously
- The theory behind today’s Neural Networks originates from the 60s
- Will we overcome these challenges with incremental advancements ?
- Do we need another breakthrough in Machine Learning and Neural Networks ?
- To achieve the ultimate goal of a fully autonomous cyber defense

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