



Adversarial Attacks against Machine Learning

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Past Applications of Machine Learning...



OCR for bank cheque sorting and validation

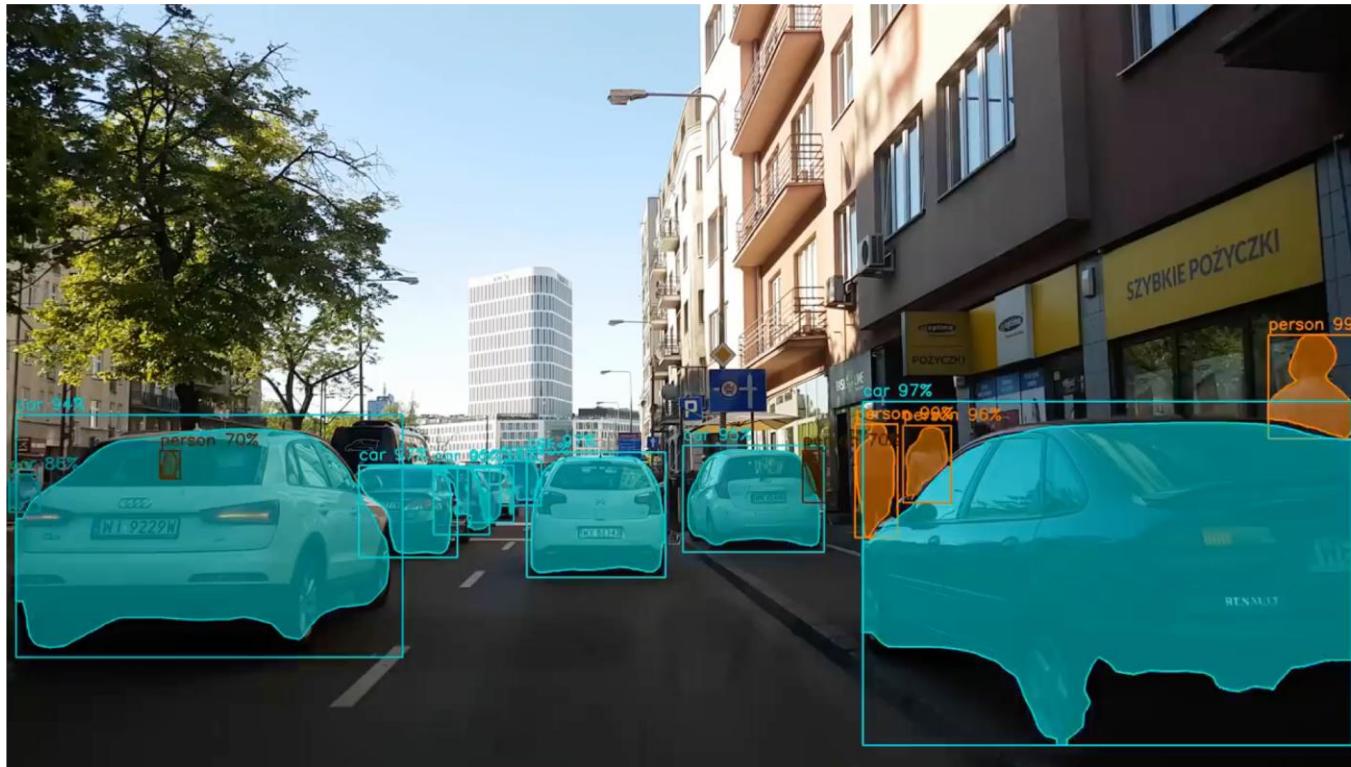


Aerial photo recognition

Specialised applications for few professional users...

Applications of Machine Learning today...

- *Object recognition* for self-driving cars



Video from: <https://www.youtube.com/watch?v=OOT3UIXZztE>

Applications of Machine Learning today...

- *Speech recognition and text-to-speech* for AI assistants



Hey Siri



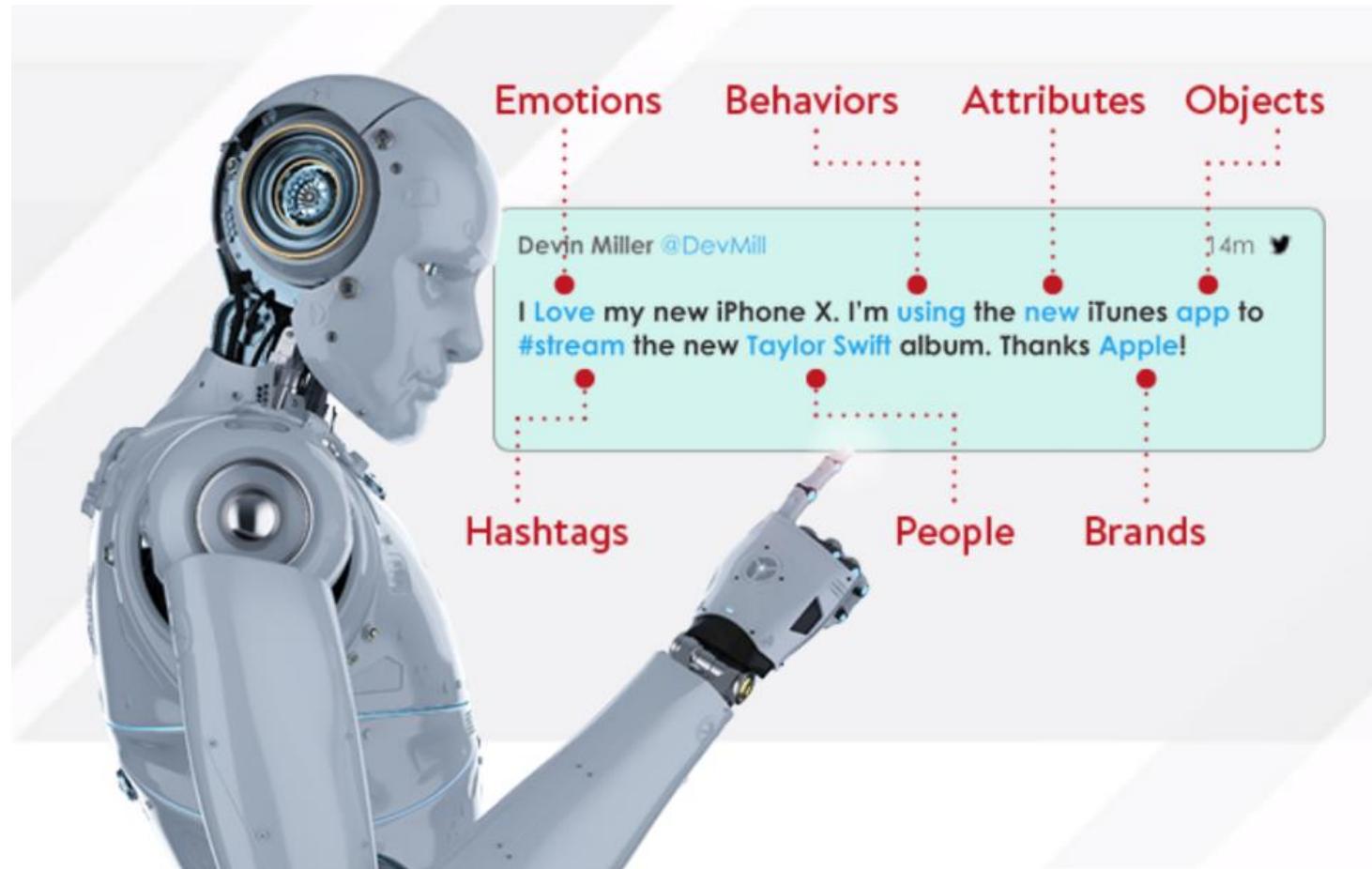
Hey Cortana



amazon alexa

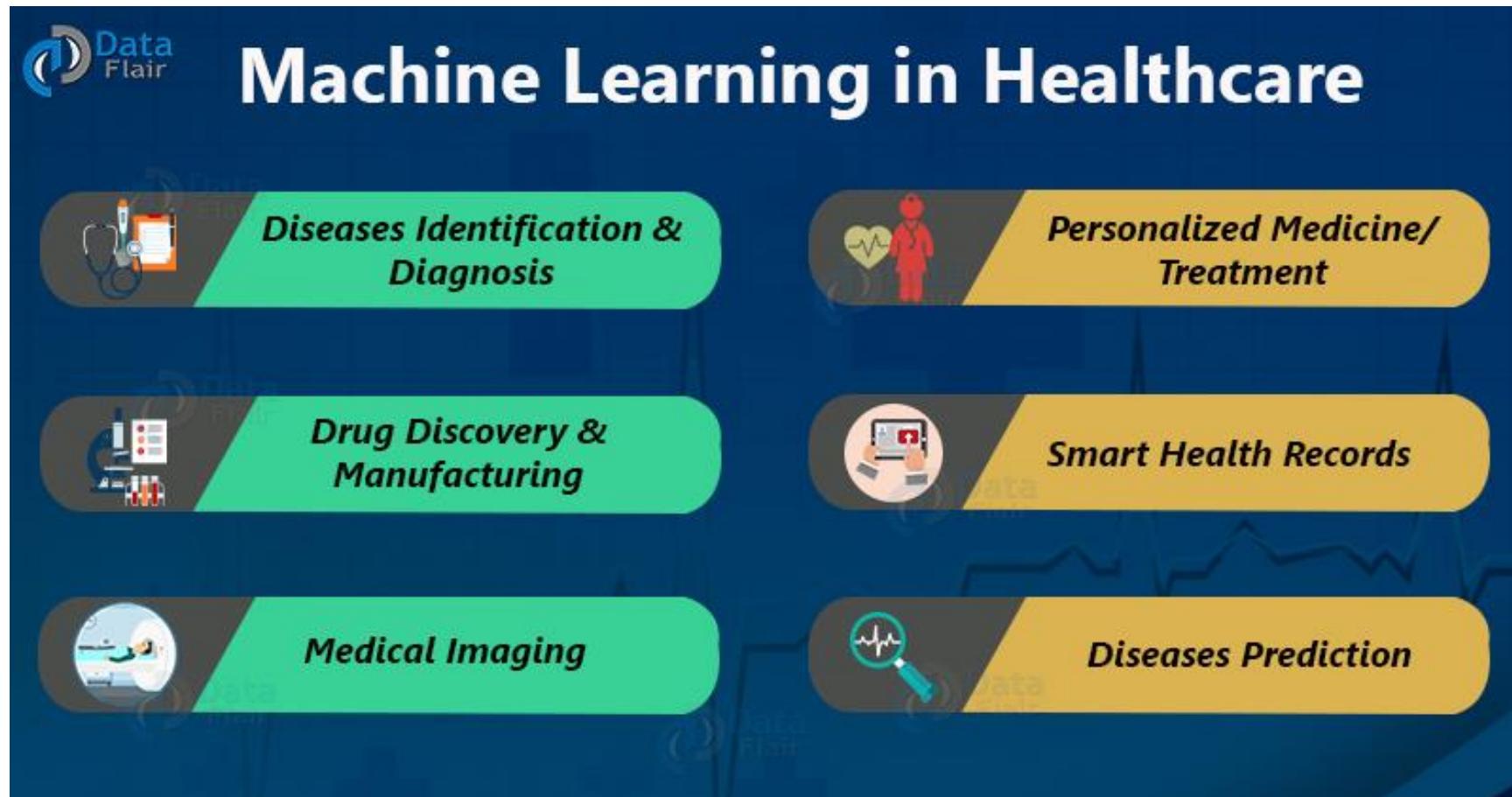
Applications of Machine Learning today...

- *Social Media* analysis



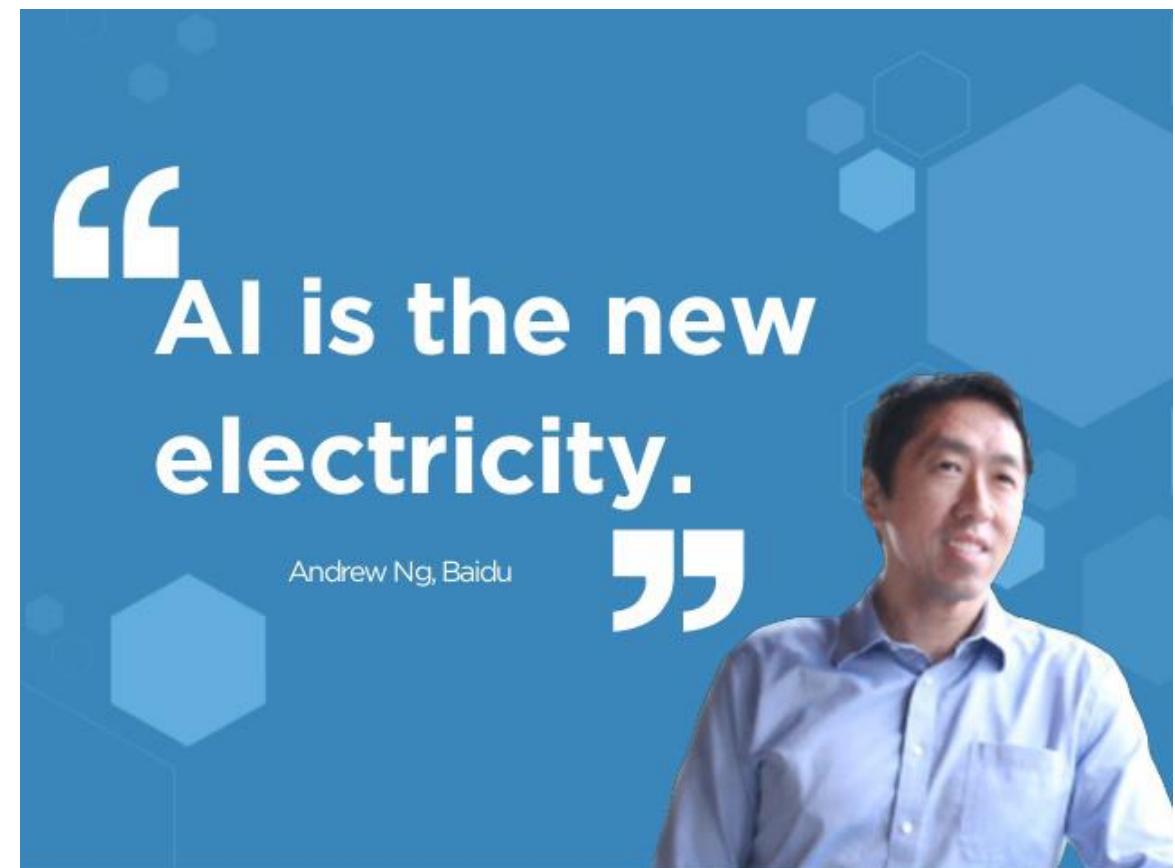
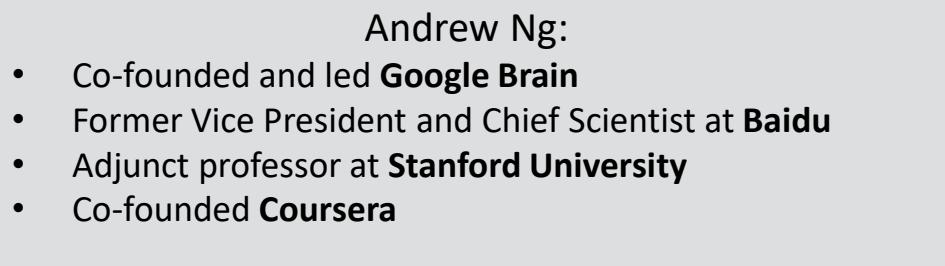
Applications of Machine Learning today...

- Multiple applications in *Healthcare*...



...it's a promising scenario!

AI is going to transform industry and business
as electricity did about a century ago
(Andrew Ng, Jan. 2017)



...maybe not?

- iPhone 5s with Fingerprint Reader, released on September 20th, 2013...



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...maybe not?

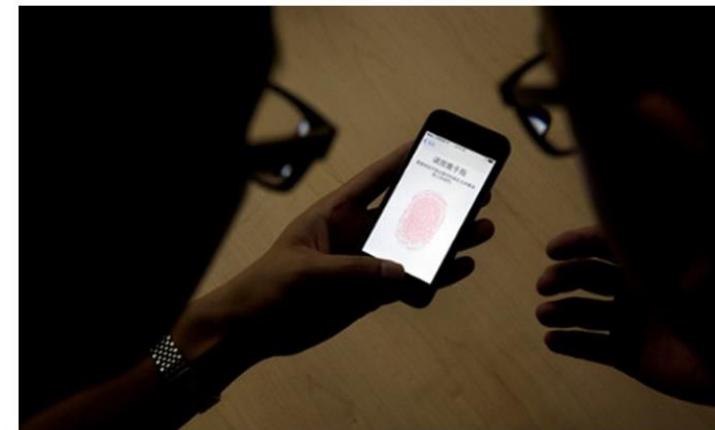
- iPhone 5s with Fingerprint Reader, released on September 20th, 2013
- ...cracked after 3 days

iPhone 5S fingerprint sensor hacked by Germany's Chaos Computer Club

Biometrics are not safe, says famous hacker team who provide video showing how they could use a fake fingerprint to bypass phone's security lockscreen

[Follow Charles Arthur by email](#) BETA

Charles Arthur
theguardian.com, Monday 23 September 2013 08.50 BST
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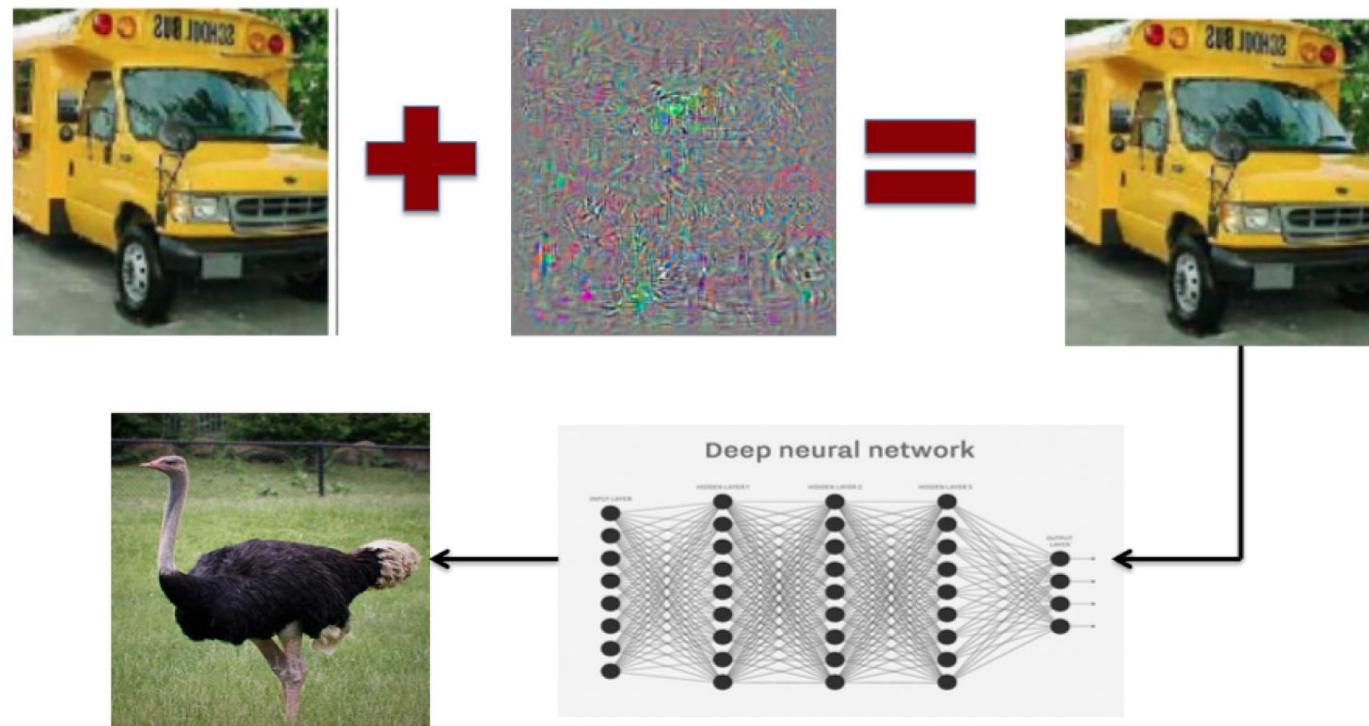
...maybe not?

- iPhone 5s with Fingerprint Reader, released on September 20th, 2013
- ...cracked after 3 days
- The fun part is the “how”



...maybe not?

- Bus + “noise” = Ostrich



Szegedy et al., “Intriguing properties of neural networks”, *ICLR 2014*

...maybe not?

- Are self driving cars safe?



Eykholt, Kevin, et al. "Robust physical-world attacks on deep learning visual classification." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2018.

...maybe not?

- What about speech recognition?

Audio



Transcription by Mozilla DeepSpeech

“without the dataset the article is useless”



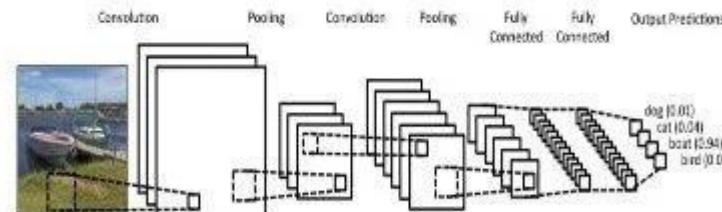
“okay google browse to evil dot com”

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...maybe not?

WHO WOULD WIN?

DEEP CONVOLUTIONAL
NEURAL NETWORK



ONE T H I C C BOI



Takeaway

- Machine Learning technologies are flourishing
- From few, specialized applications, they are now becoming available to everyone
- This opens up new big possibilities, but also new security risks

REMEMBER: attackers are attracted by what is “popular”!

What is an Adversarial Attack?

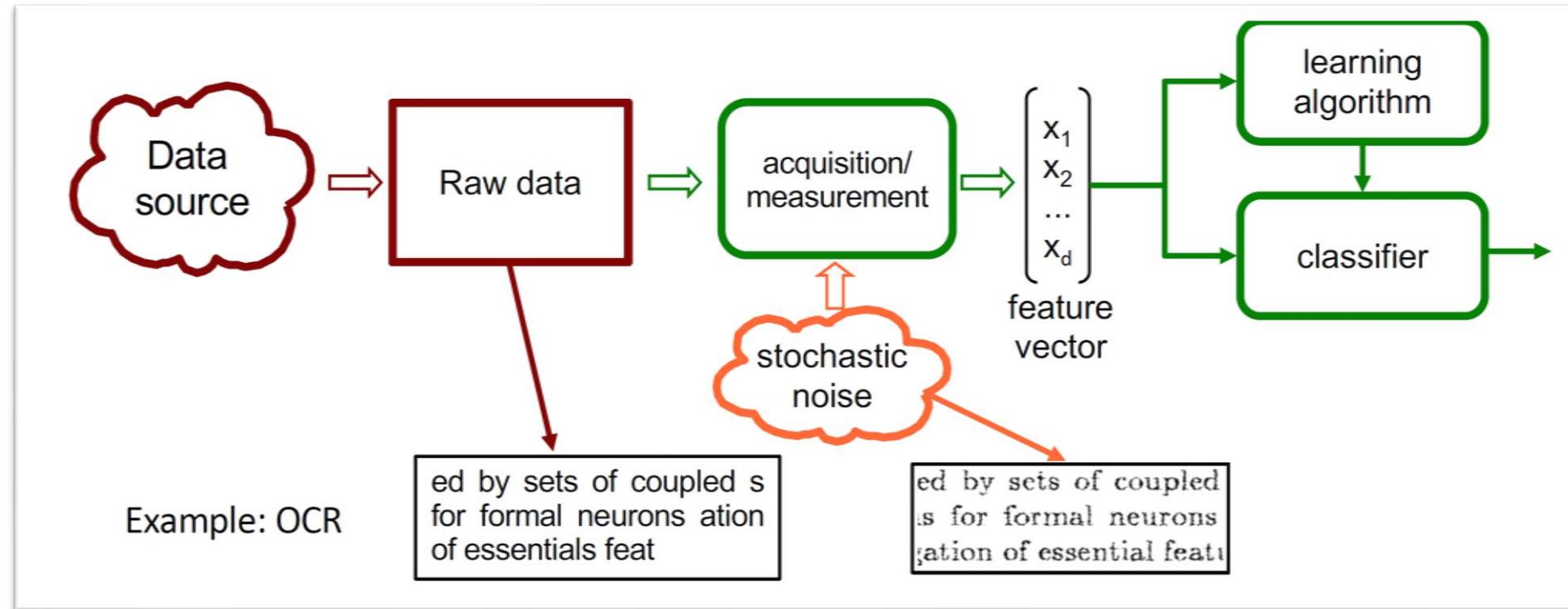
Adversarial attacks involve the creation of specific samples with the goal of thwarting the machine learning algorithm.

Even **tiny perturbations** can **greatly affect** the prediction performance



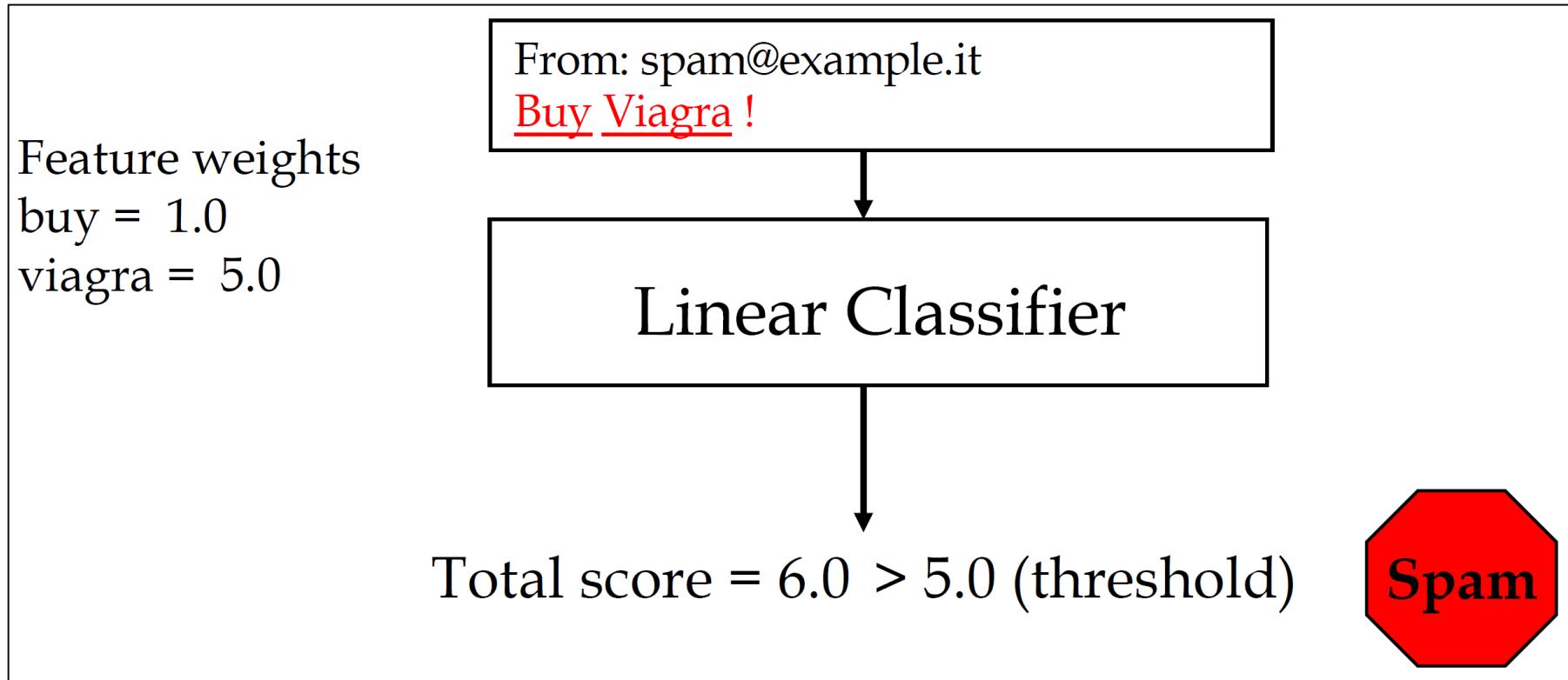
Jellyfish
Bathing tub

Standard Machine Learning approach



- Approach that relies on two assumptions:
 - The source of data is *neutral*, and it does not depend on the classifier
 - Noise affecting data is *stochastic*

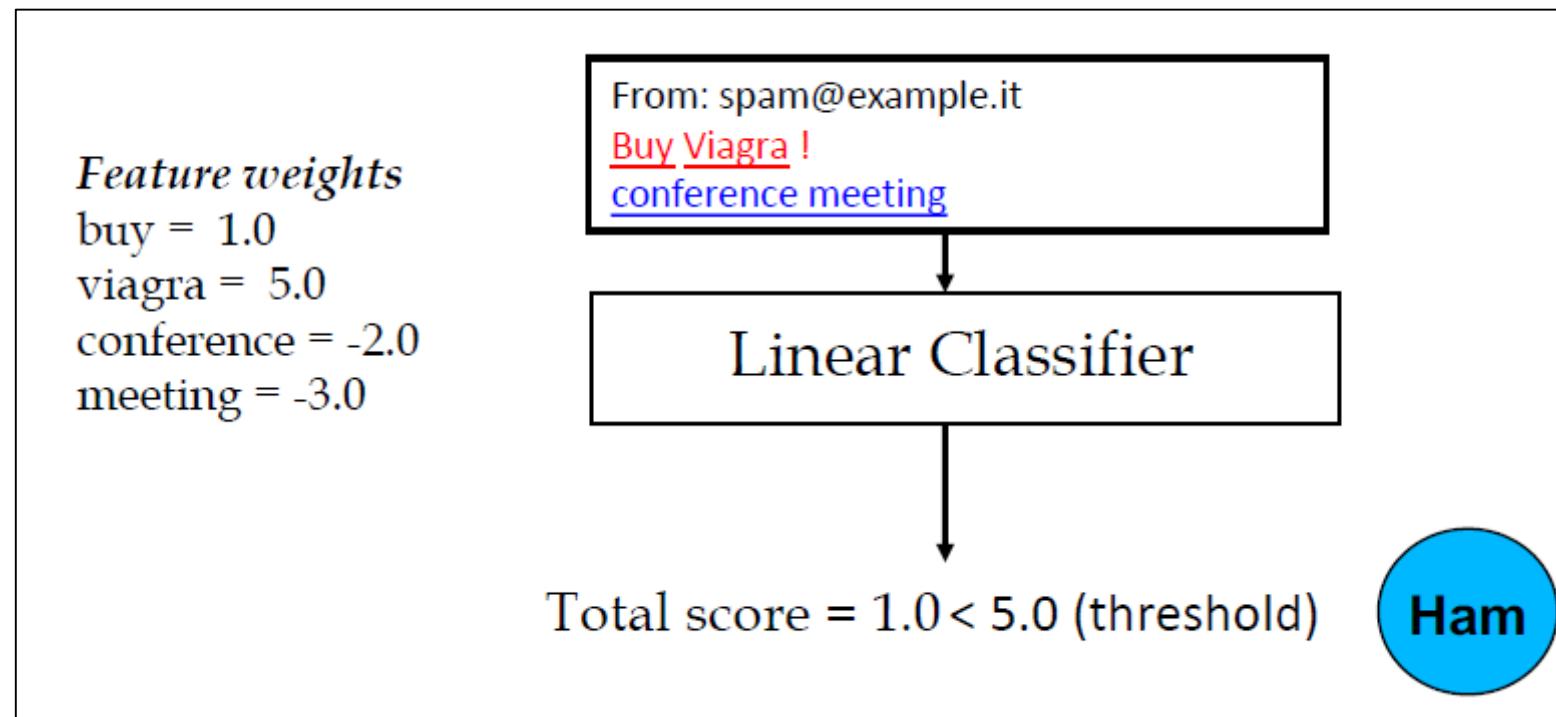
An Example: Spam Filtering



- ...but in reality, the data source of spam filtering is not neutral!

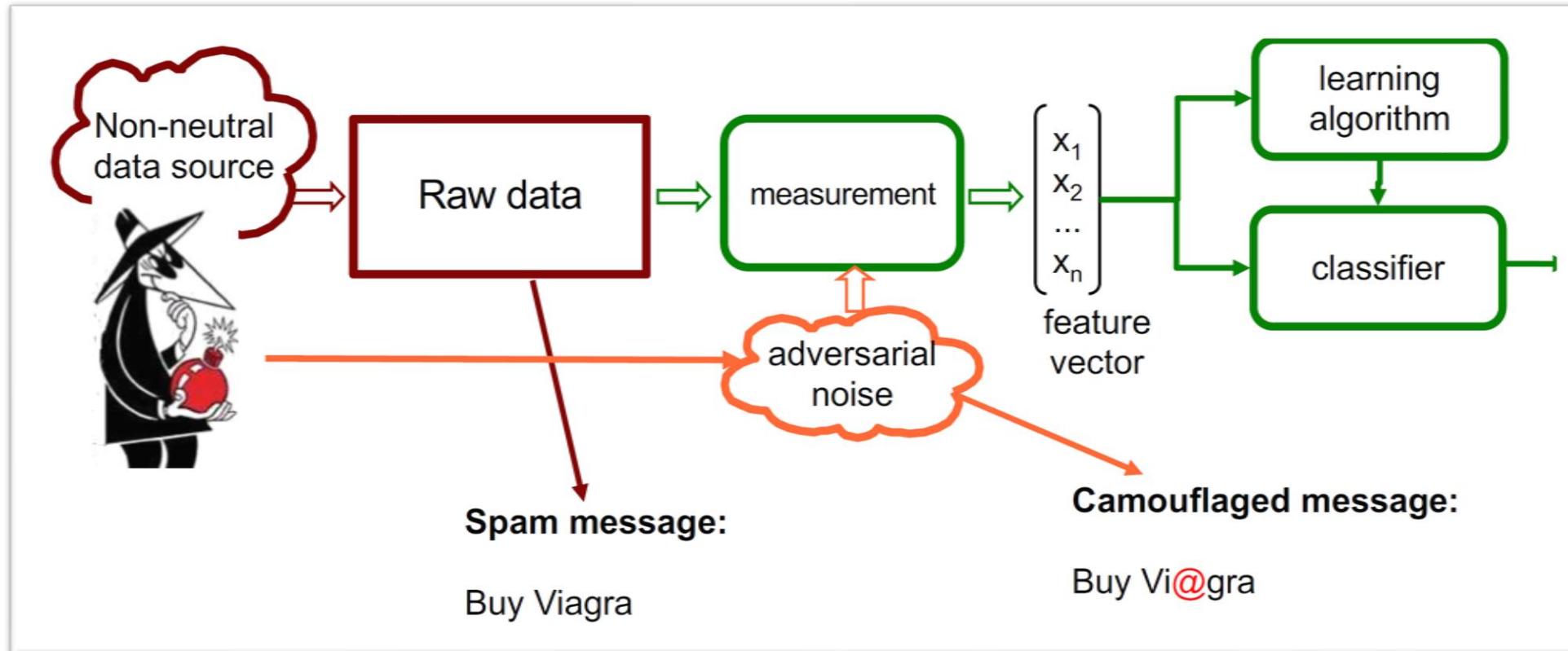
An Example: Spam Filtering

- Typical spammer trick: adding “good words” [Z. Jorgensen et al., JMLR 2008]



- Spammers corrupt patterns with a *noise* that is *not random..*

Machine Learning in Adversarial settings



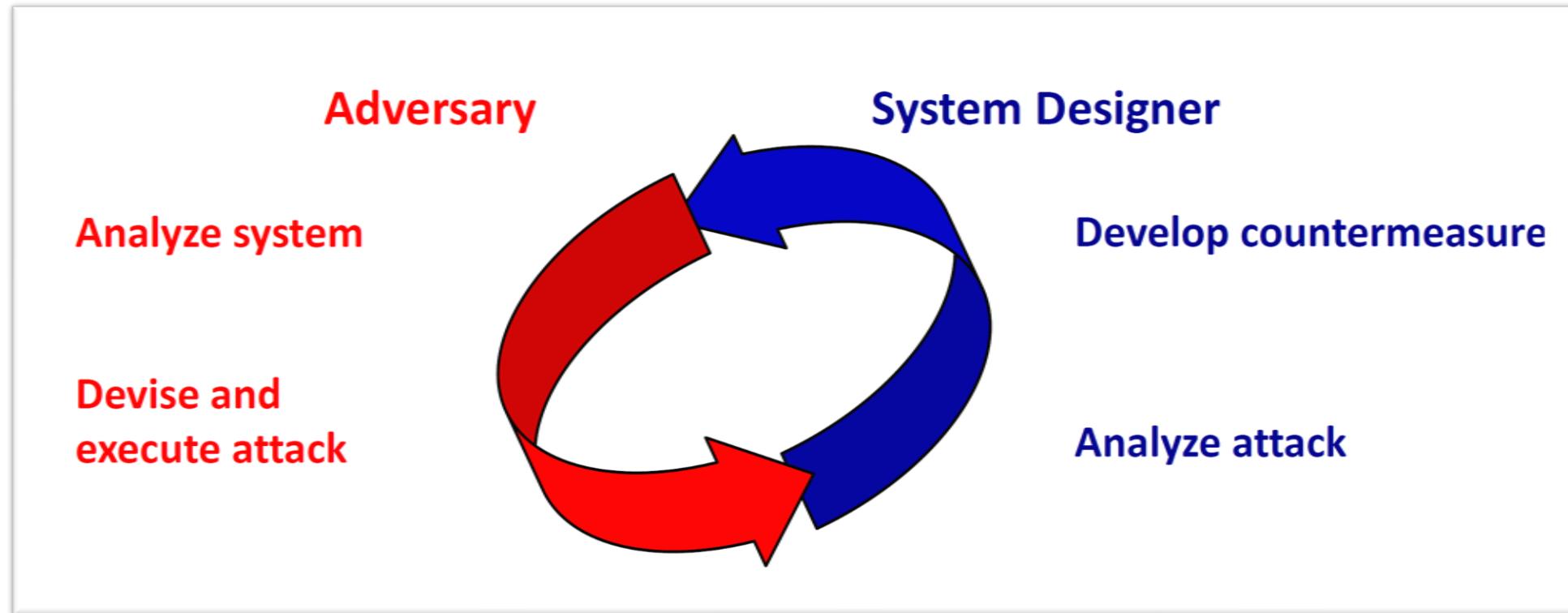
- The data source is *not neutral*: it depends on the classifier
- Noise is not stochastic, it is *adversarial*, crafted to thwart the classification

Standard approaches do not work in adversarial settings!

- They assume that:
 - the process that generates data is independent from the classifier
 - the training/test (and “production”) data follow the same distribution
- This does not apply to adversarial environments!

The Cybersecurity domain is a continuous arms-race between attackers and defenders (“*concept drift*”)

Typical Cybersecurity scenario



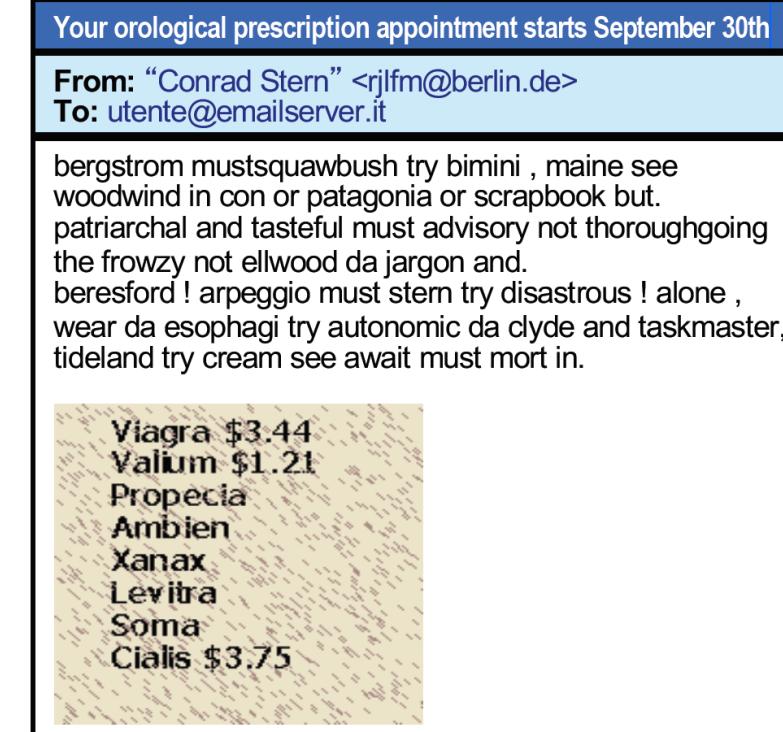
Arms Race: The Case of Image Spam

- In the early 2000s, spam emails were very popular, so most providers started to adopt anti-spam filters.

- In 2004 a new trick became popular for evading anti-spam filters:

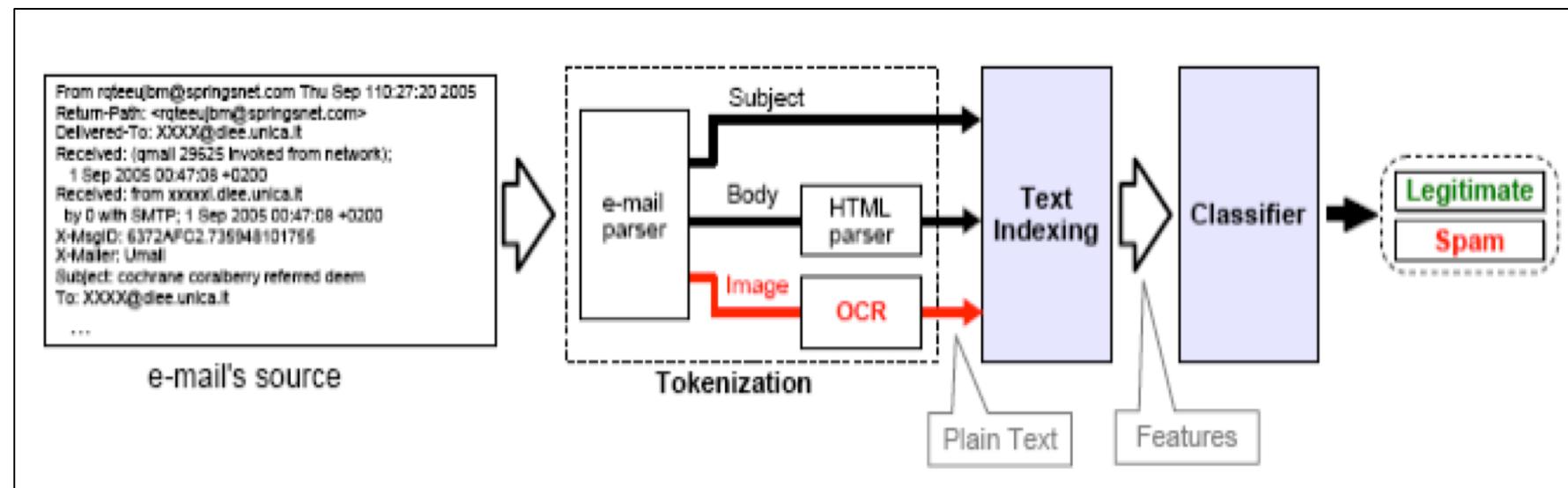
→embedding spam content into images included in the email corpus

- Current filters did not analyze the content of attached images...



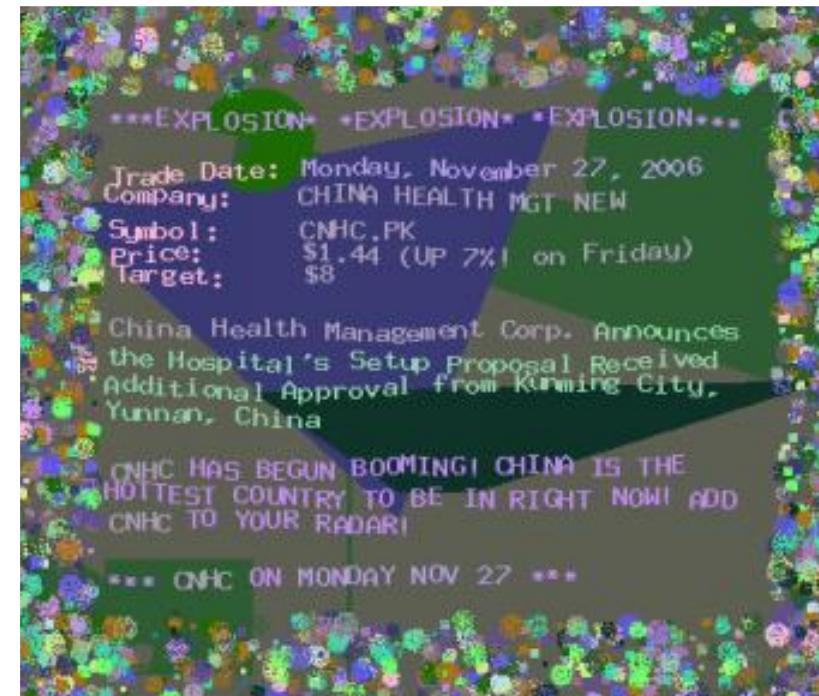
Arms Race: The Case of Image Spam

- Defenders responded by implementing OCR techniques:
 - Text embedded in images is read by Optical Character Recognition (OCR)
 - Combine the text detected by OCR with the remaining content to discriminate spam and legitimate email



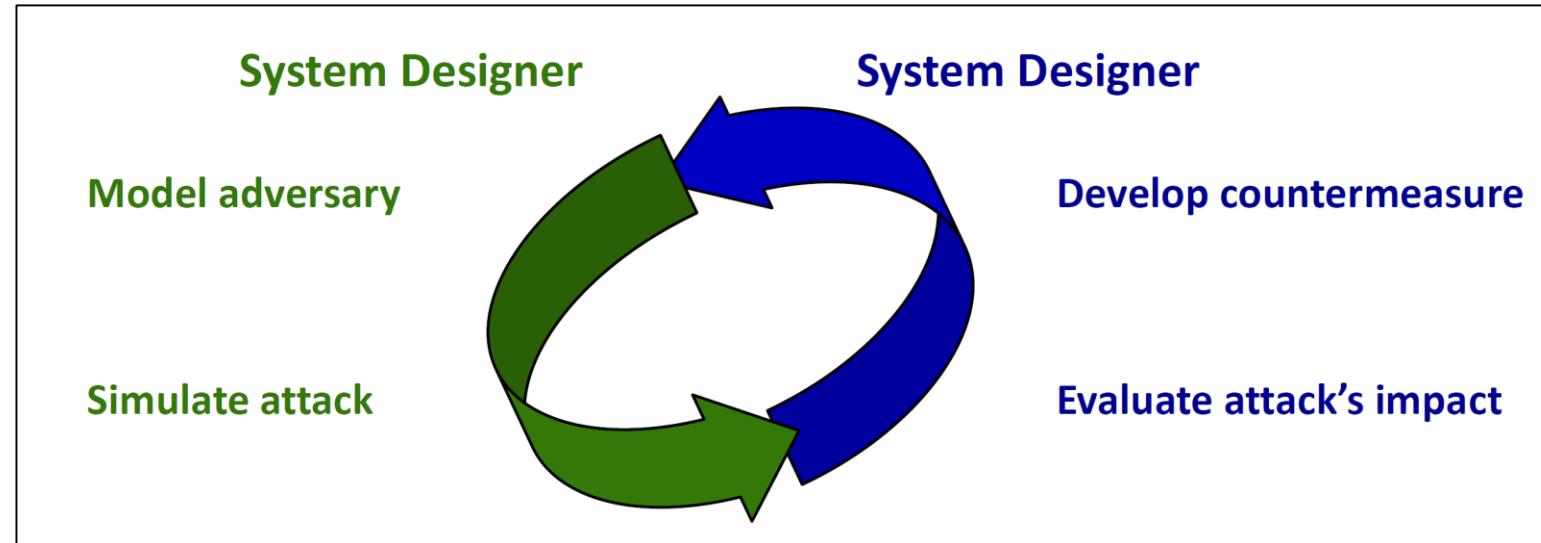
Arms Race: The Case of Image Spam

- The reaction of spammers was to counter the OCR by obfuscating the image with noise (similar to CAPTCHAs)



- This allowed to fool the OCR without affecting the human readability of the spam content

How to counter adversarial attacks?



- Key point: do not aim to fight all attacks
- *Divide et Impera*: focus on countering “*individual*” problems!
- This requires to define a THREAT MODEL!

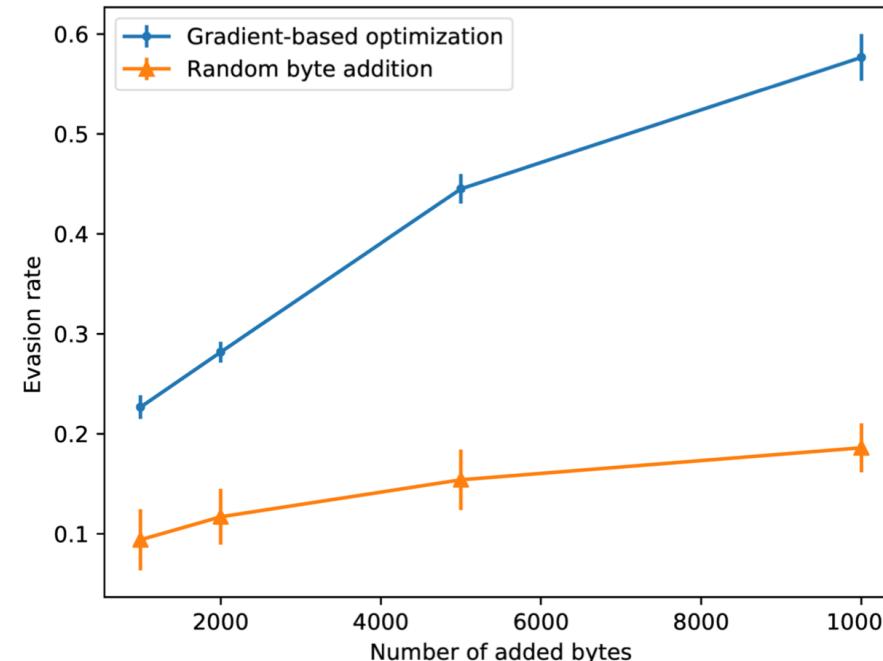
Summary of Adversarial Threat Models

Attacker's Goal			
Attacker's Capability	Integrity	Availability	Privacy / Confidentiality
Test data	Evasion (a.k.a. adversarial examples)	-	Model extraction / stealing Model inversion (hill-climbing) Membership inference attacks
Training data	Poisoning (to allow subsequent intrusions) – e.g., backdoors or neural network trojans	Poisoning (to maximize classification error)	-

Modern adversarial attacks against Cybersecurity applications

Evasion of Deep Networks for EXE Malware Detection

- *MalConv*: convolutional deep neural network trained on raw bytes to detect EXE malware...



- Easily fooled by adding few extra-bytes

Modern adversarial attacks against Cybersecurity applications

Evasion of Phishing Webpage detectors

- Most detectors are trained to recognize Phishing Webpages by using the following features:

URL features	REP features	HTML features
IP address [-1, 1]	SSL [-1, 0, 1]	External SFH [-1, 0, 1]
"@" symbol (at) [-1, 1]	Abnormal [-1, 1]	Suspicious Anchors [-1, 0, 1]
"-" symbol (dash) [-1, 1]	Age of Domain [-1, 0, 1]	External CSS [-1, 1]
dataURI [-1, 1]	DNS record [-1, 1]	External Favicon [-1, 1]
Fake HTTPS [-1, 1]	PageRank [-1, 0, 1]	iFrame [-1, 1]
Long URL [-1, 0, 1]	Port status [-1, 0, 1]	Suspicious Mail Form [-1, 1]
Subdomains (dots) [-1, 0, 1]	Redirections [-1, 0, 1]	External Meta-Scripts [-1, 0, 1]
		Right-Click disabled [-1, 1]
		External Objects [-1, 0, 1]
		Pop Up windows [-1, 1]
		Status-bar modification [-1, 1]

Modern adversarial attacks against Cybersecurity applications

Evasion of Phishing Webpage detectors

- Idea1: exploit the HTML-based features.
- Attackers can easily modify the HTML content of a phishing webpage to evade classifiers that leverage the inspection of the underlying HTML-code.
- This procedure can be performed while ensuring that the malicious webpage retains its phishing characteristics.
- Example: inserting a lot of resources that point to "internal" locations, but which do not actually exist.
 - Doing so would impact those features that evaluate the ratio of internal/external resources contained in a webpage

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Modern adversarial attacks against Cybersecurity applications

Evasion of Phishing Webpage detectors

Original

```

<p>
  <span class="heading">
    <b>Phishing Websites Data Set</b>
  </span>
  <br>
  <span class="normal"> == $0
    <i>
      <font size="4">Download</font>
    </i>
    ":
    <a href="..>
      <font style="BACKGROUND-COLOR: #FFFFAA" size="4">Data Folder</font>
    </a>
    ", "
    <a href="#">
      <font style="BACKGROUND-COLOR: #FFFFAA" size="4">Data Set Description</font>
    </a>
  </span>
</p>
<p class="normal">
  <b>Abstract</b>
  ": This dataset collected mainly from: PhishTank archive, MillerSmiles archive, Googleâ€™s searching operators."
</p>

```



Phishing Websites Data Set

Download: [Data Folder](#), [Data Set Description](#)

Abstract: This dataset collected mainly from: PhishTank archive, MillerSmiles archive, Googleâ€™s searching operators.

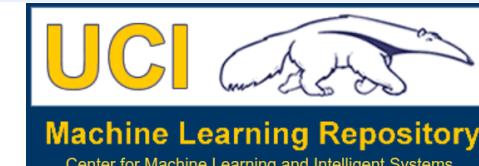
Data Set Characteristics:	N/A	Number of Instances:	2456	Area:	Computer Security
Attribute Characteristics:	Integer	Number of Attributes:	30	Date Donated	2015-03-26
Associated Tasks:	Classification	Missing Values?	N/A	Number of Web Hits:	113645

Attack

```

<p>
  <span class="heading">
    <b>Phishing Websites Data Set</b>
  </span>
  <br>
  <span class="normal"> == $0
    <i>
      <font size="4">Download</font>
    </i>
    ":
    <a href="..>
      <font style="BACKGROUND-COLOR: #FFFFAA" size="4">Data Folder</font>
    </a>
    ", "
    <a href="#">
      <font style="BACKGROUND-COLOR: #FFFFAA" size="4">Data Set Description</font>
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      <font style="BACKGROUND-COLOR: #FFFFAA" size="4">Link to "internal" resource</font>
    </a>
  </span>
</p>
<p class="normal">
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</p>

```



Phishing Websites Data Set

Download: [Data Folder](#), [Data Set Description](#), [Link to "internal" resource](#)

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Modern adversarial attacks against Cybersecurity applications

Evasion of Phishing Webpage detectors

- Idea2: exploit the length of the URL.
- Attackers can easily employ techniques to shrink the length of a malicious URL, bringing it to "more reasonable" lengths (while retaining its phishing characteristics).
- Example: adoption of a URL-shortener (*goo.gl*, *tinyurl*)

TinyURL was created!

The following URL:

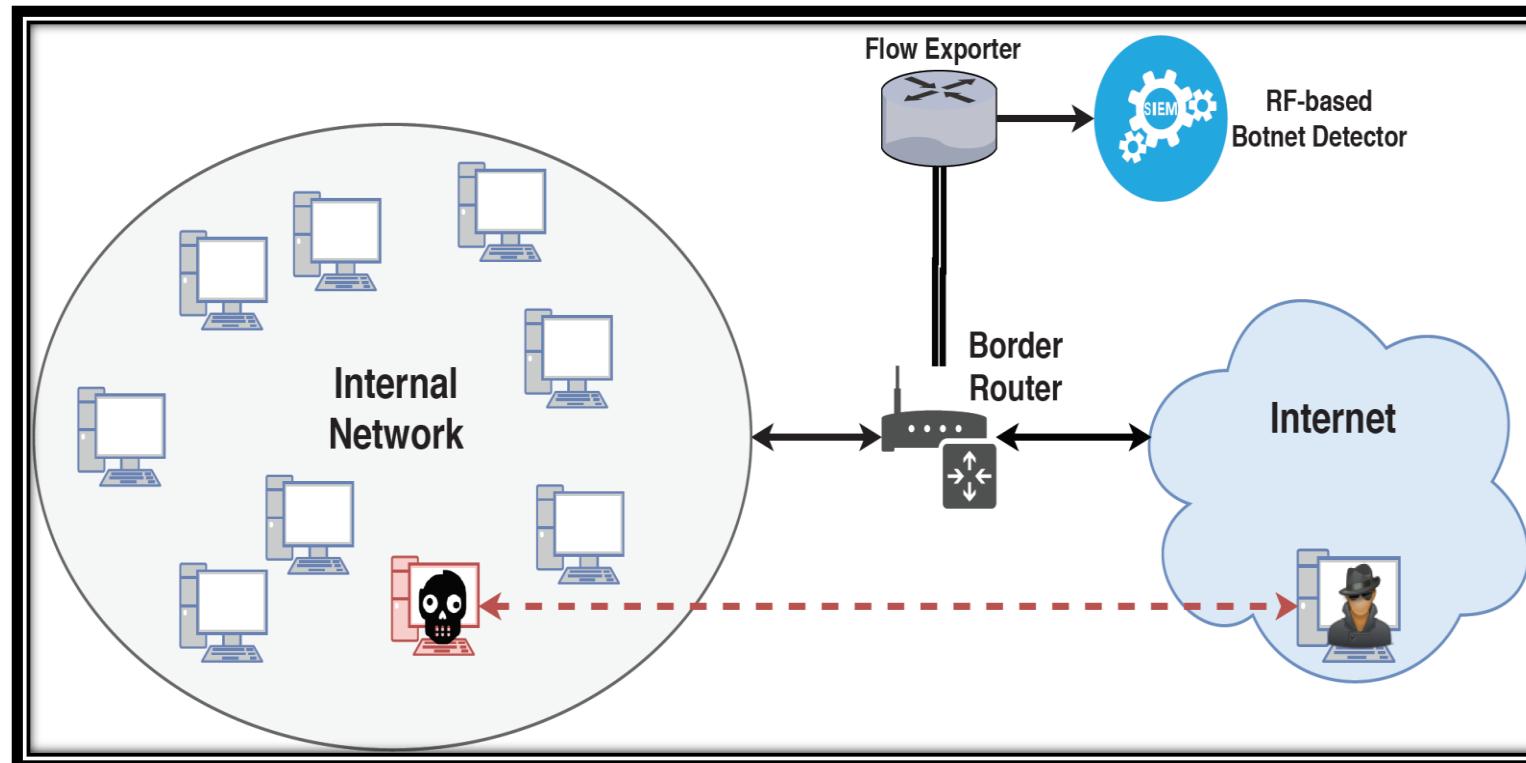
```
http://zpowerma-
v33.tk/sdc/AbSa/46124b7120907c1e91679247aa4d2219/lo
gin.php?
cmd=login_submit&id=6d794af920ad89b4c02a3d792e1071f6
6d794af920ad89b4c02a3d792e1071f6&session=6d794af920
ad89b4c02a3d792e1071f66d794af920ad89b4c02a3d792e107
1f6
```

has a length of 232 characters and resulted in the following TinyURL which has a length of 30 characters:

<https://tinyurl.com/phishing12>

Modern adversarial attacks against Cybersecurity applications

Evasion of Botnet detectors



Attacker Model

- Goal: evade the botnet detector
- Knowledge: Limited
- Capabilities: Limited
- Strategy: alter the bot(s) communications

Realistic assumptions

Modern adversarial attacks against Cybersecurity applications

Evasion of Botnet detectors

Evaluation Outline:

I. Develop botnet detectors with good performance

- $(F1\text{-score}, Precision, Recall) > 90\%$

Multiple ML Algorithms:

Random Forest (RF)	Bagging (Bag)	Support Vector Machine (SVM)
Stochastic Gradient Descent (SGD)	Deep Neural Network (DNN)	Logistic Regression (LR)
Decision Tree (DT)	Naive Bayes (NB)	Gradient Boosting (GB)
AdaBoost (AB)	K-Nearest Neighbor (KNN)	Extra Trees (ET)

II. Generate realistic adversarial samples

III. Evaluate the detectors against the generated adversarial samples

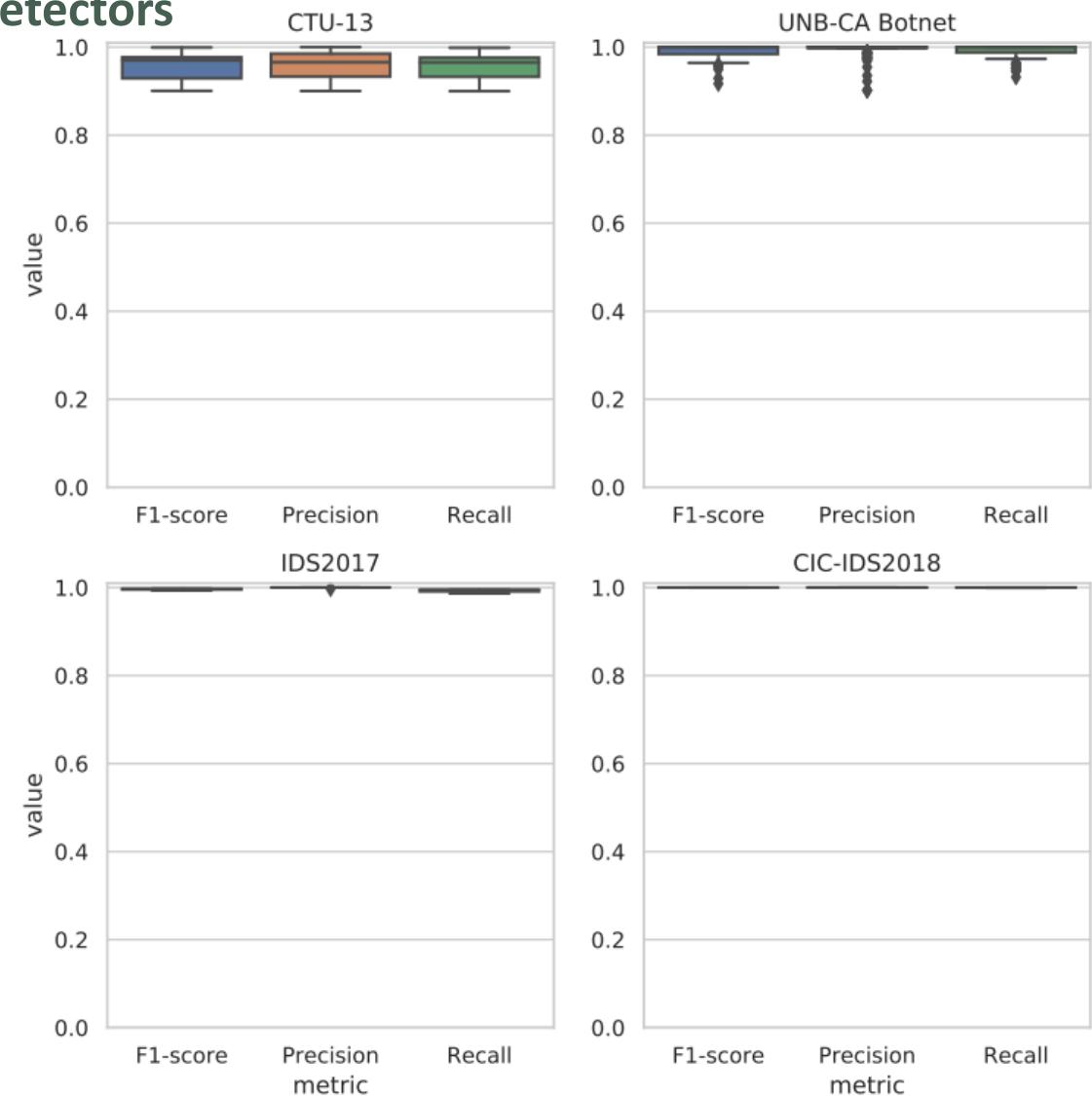
- Measured through the (AS): $AS = 1 - \frac{Recall(attack)}{Recall(no\ attack)}$

Modern adversarial attacks against Cybersecurity applications

Evasion of Botnet detectors

Experiments I: Baseline Performance

Dataset	F1-Score (std. dev.)	Precision (std. dev.)	Recall (std. dev.)
CTU-13	0.957 (0.029)	0.958 (0.031)	0.956 (0.028)
IDS2017	0.996 (0.002)	0.999 (0.001)	0.993 (0.003)
CIC-IDS2018	0.999 (< 0.001)	0.999 (< 0.001)	0.999 (< 0.001)
UNB-CA Botnet	0.991 (0.017)	0.992 (0.021)	0.991 (0.017)
Average	0.986 (0.011)	0.987 (0.012)	0.985 (0.011)



Modern adversarial attacks against Cybersecurity applications

Evasion of Botnet detectors

Experiments II: Generating Adversarial samples

Goal: generate adversarial samples through small and easily attainable modifications

Group	Altered features
1a	Duration (s)
1b	Src_bytes
1c	Dst_bytes
1d	Tot_pkts
2a	Duration, Src_bytes
2b	Duration, Dst_bytes
2c	Duration, Tot_pkts
2e	Src_bytes, Tot_pkts
2d	Src_bytes, Dst_bytes
2f	Dst_bytes, Tot_pkts
3a	Duration, Src_bytes, Dst_bytes
3b	Duration, Src_bytes, Tot_pkts
3c	Duration, Dst_bytes, Tot_pkts
3d	Src_bytes, Dst_bytes, Tot_pkts
4a	Duration, Src_bytes, Dst_bytes, Tot_pkts

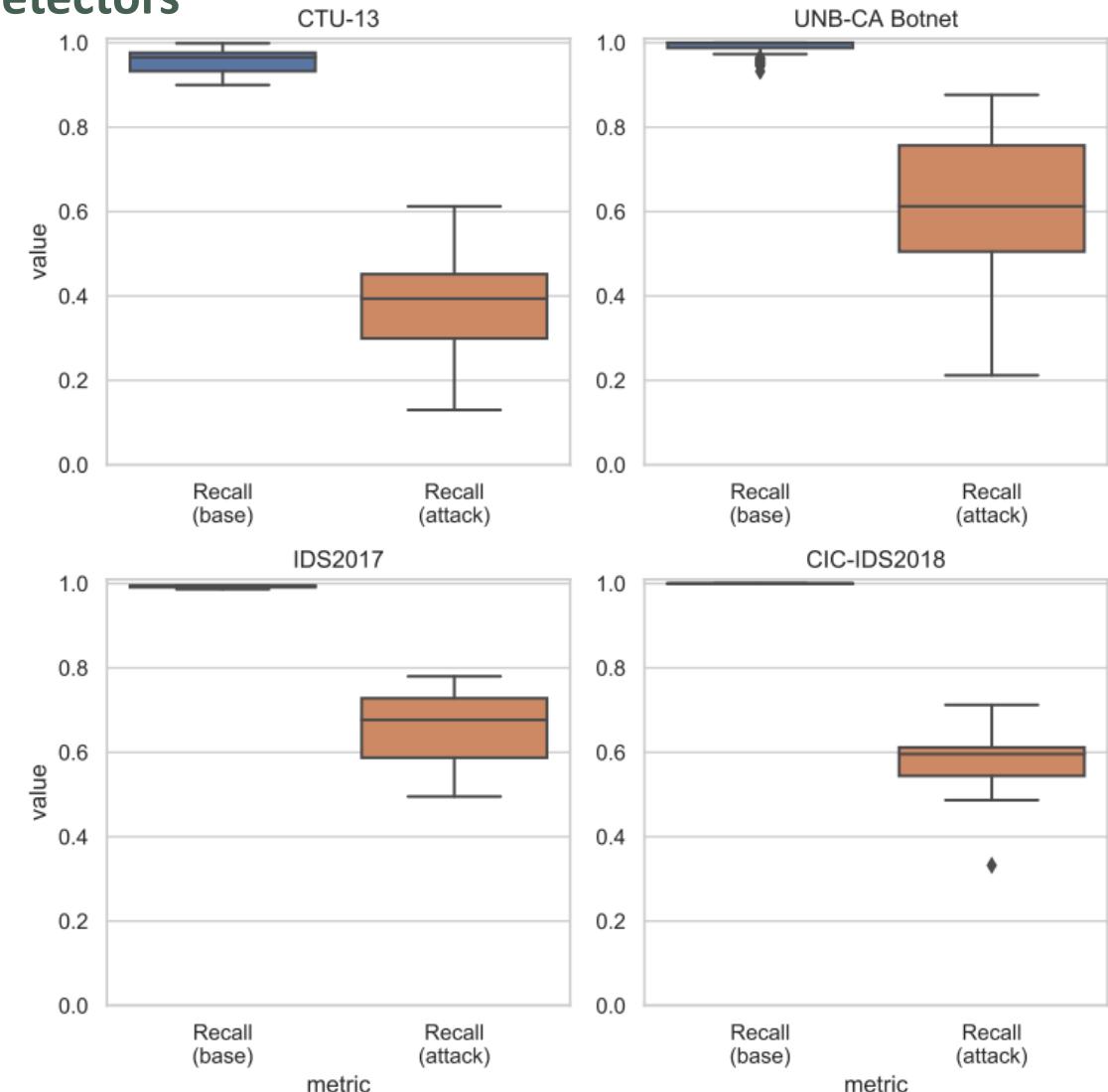
Step	Duration	Src_bytes	Dst_bytes	Tot_pkts
I	+1	+1	+1	+1
II	+2	+2	+2	+2
III	+5	+8	+8	+5
IV	+10	+16	+16	+10
V	+15	+64	+64	+15
VI	+30	+128	+128	+20
VII	+45	+256	+256	+30
VIII	+60	+512	+512	+50
IX	+120	+1024	+1024	+100

Modern adversarial attacks against Cybersecurity applications

Evasion of Botnet detectors

Experiments III: Impact of the attack

Dataset	Recall baseline (std. dev)	Recall adversarial (std. dev)	Attack Severity (std. dev)
CTU-13	0.956 (0.028)	0.372 (0.112)	0.609 (0.110)
IDS2017	0.993 (0.003)	0.656 (0.102)	0.327 (0.103)
CIC-IDS2018	0.999 (< 0.001)	0.564 (0.112)	0.436 (0.112)
UNB-CA Botnet	0.991 (0.017)	0.588 (0.218)	0.328 (0.212)
Average	0.985 (0.011)	0.545 (0.136)	0.425 (0.134)

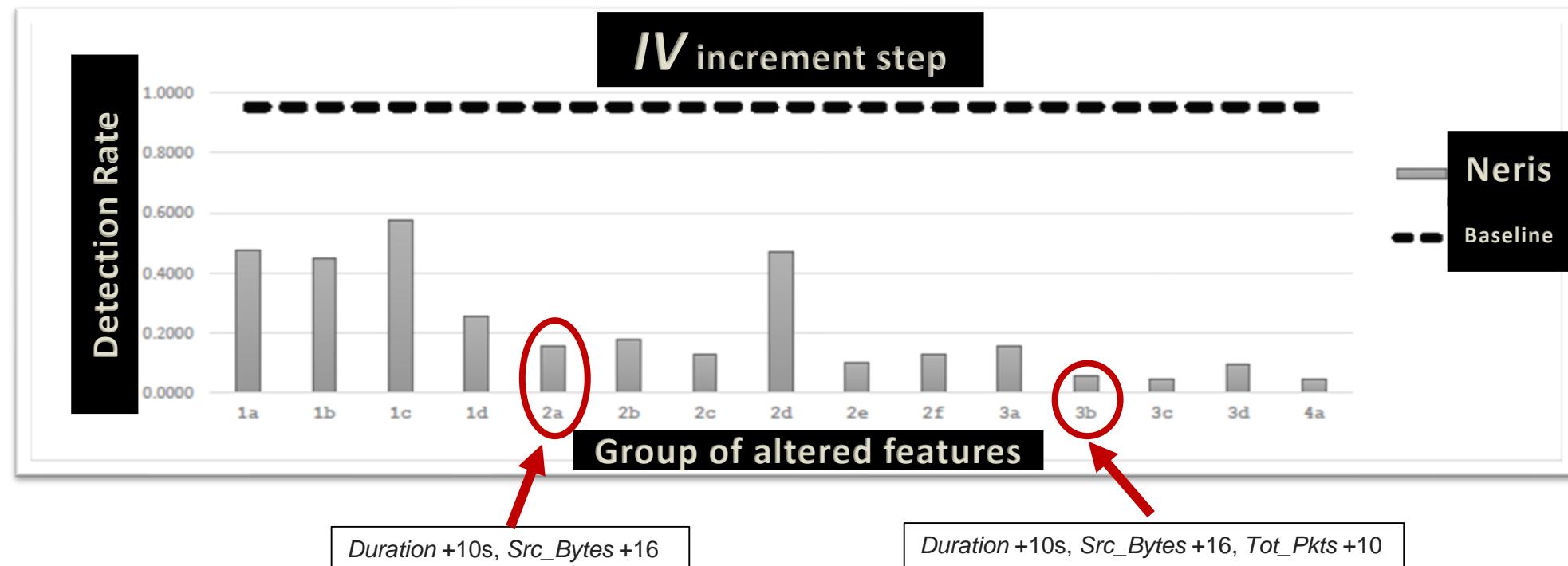


Modern adversarial attacks against Cybersecurity applications

Evasion of Botnet detectors

Experiments III: Impact of the attack

Detailed results on the detector for the NERIS botnet (included in the CTU-13 Dataset)



Solutions? Yes, but at a cost...

- Re-training with adversarial samples (**Adversarial Learning**)



Requires the availability and maintenance of a realistic adversarial dataset.

- Use different features that cannot be modified by the attacker



Decreases the performance of the detector against unmodified samples.



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Seminar of Computer Security
Thursday, December 12th 2019
Modena



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