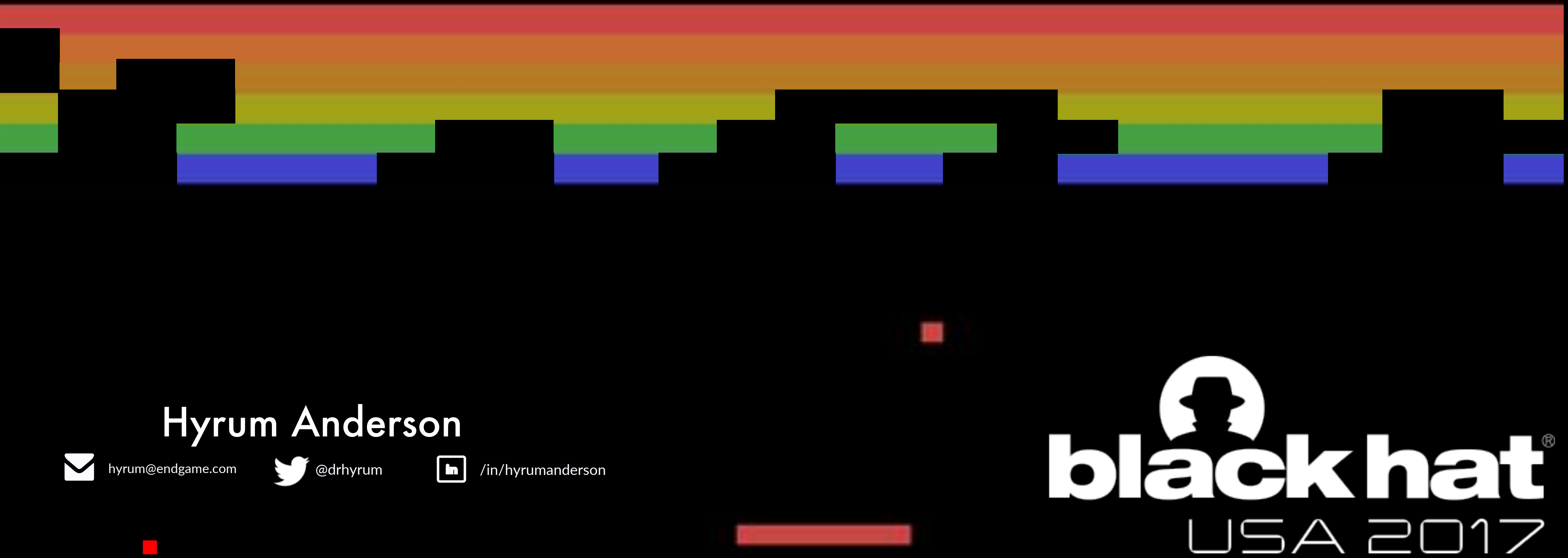
Bot vs. Bot: Evading Machine Learning Malware Detection



Hyrum Anderson

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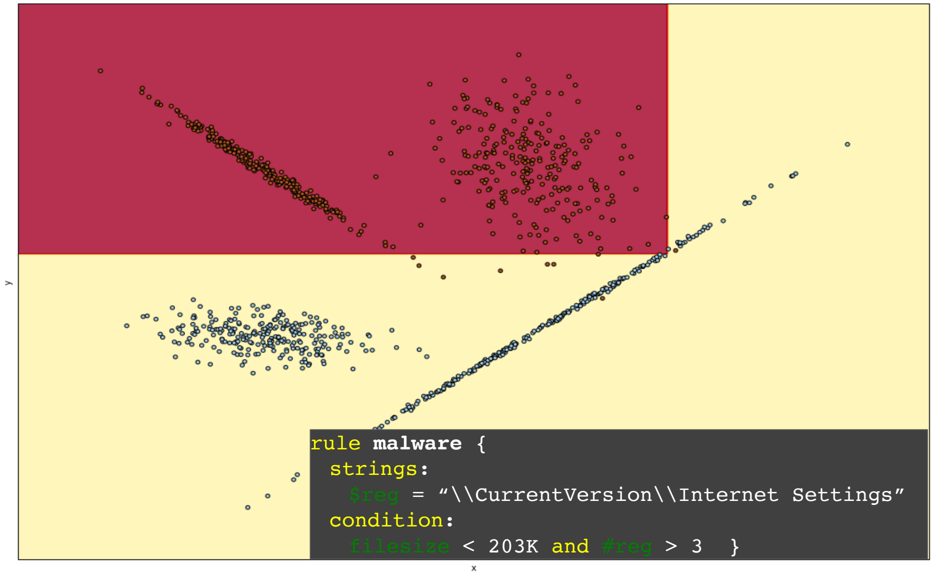
black hat®
USA 2017

The Promise of Machine Learning

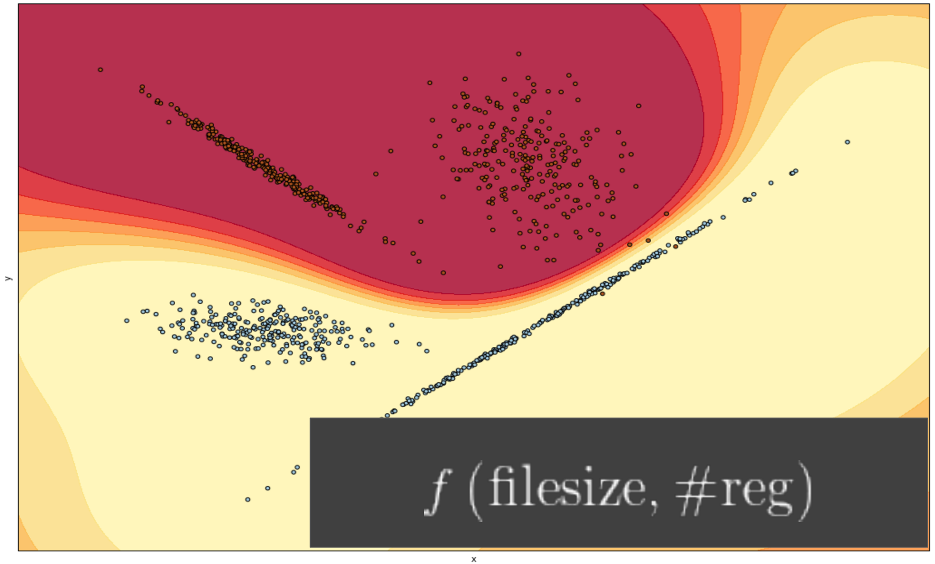
- Learn *from data* what constitutes malicious content or behavior

- Discriminatory patterns learned automatically, not obviously constructed by hand

- Generalize to never-before-seen samples and variants…
  - …so long as data used for "training" is representative of deployment conditions
  - motivated adversaries actively trying to invalidate this assumption

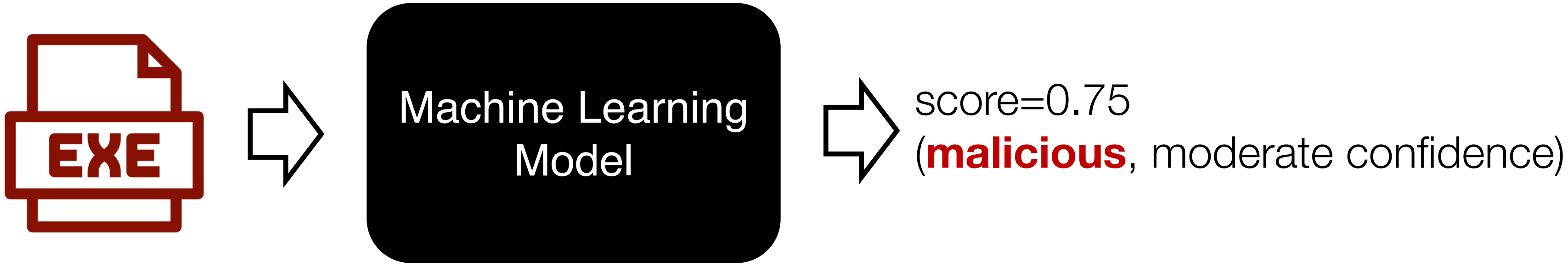


```
rule malware {
  strings:
    $reg = "\\CurrentVersion\\Internet Settings"
  condition:
    filesize < 203K and #reg > 3  }
```



Goal: Can You Break Machine Learning?

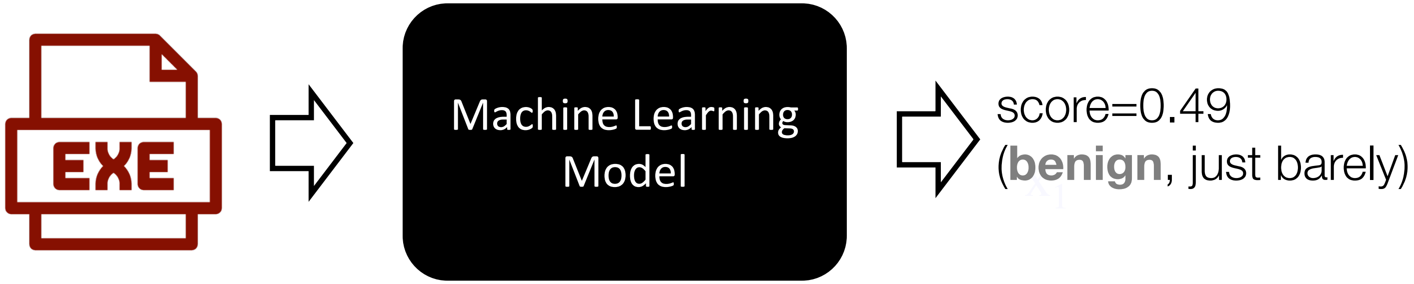
- Static machine learning model trained on millions of samples



Machine Learning Model

score=0.75
(**malicious**, moderate confidence)

- Simple structural changes that don't change behavior
  - unpack
  - '.text' -> '.foo' (remains valid entry point)
  - create '.text' and populate with '.text from calc.exe'

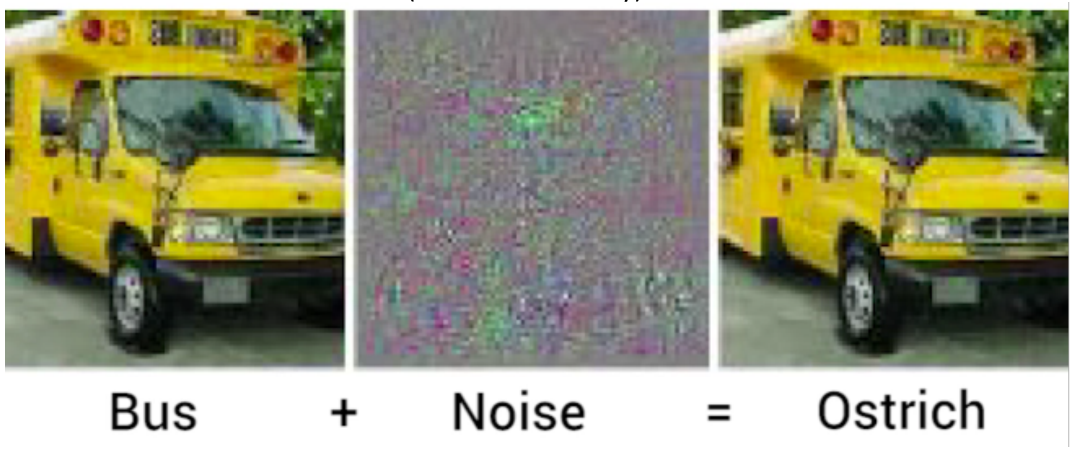


Machine Learning Model

score=0.49
(**benign**, just barely)

Adversarial Examples

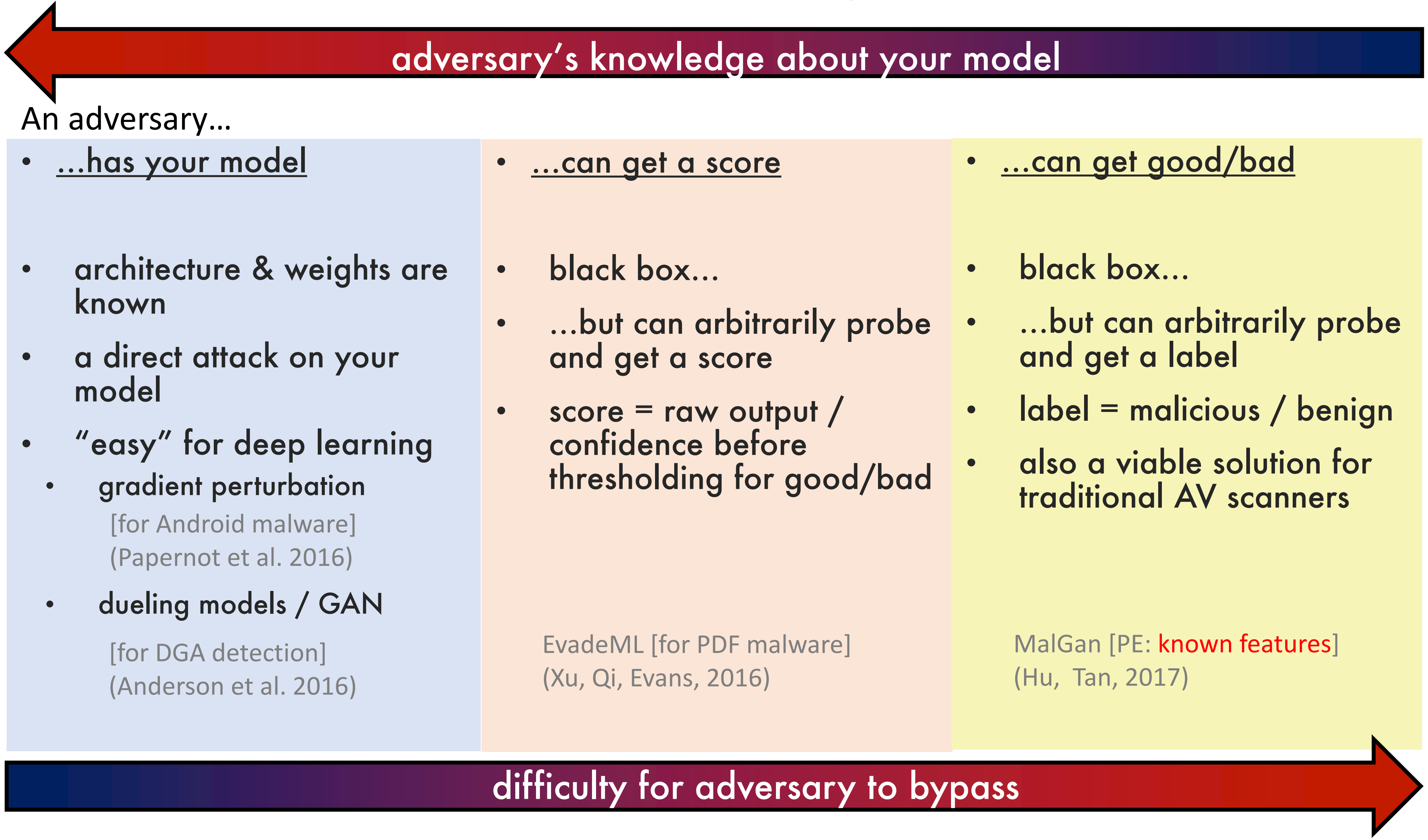
(scaled for visibility)



- Machine learning models have blind spots / hallucinate (modeling error)
- Depending on model and level of access, they can be straightforward to exploit
  - e.g., deep learning is fully differentiable
    (directly query what perturbation would best bypass model)
- Adversarial examples can generalize **across** models / model types (Goodfellow 2015)
  - blind spots in MY model may also be blind spots in YOUR model

image credit: http://www.popsci.com/byzantine-science-deceiving-artificial-intelligence

Taxonomy of Attacks Against ML



adversary's knowledge about your model

An adversary…

- …has your model
- architecture & weights are known
- a direct attack on your model
- "easy" for deep learning
  - gradient perturbation

    [for Android malware] (Papernot et al. 2016)
  - dueling models / GAN

    [for DGA detection] (Anderson et al. 2016)

- …can get a score
- black box…
- …but can arbitrarily probe and get a score
- score = raw output / confidence before thresholding for good/bad

EvadeML [for PDF malware] (Xu, Qi, Evans, 2016)

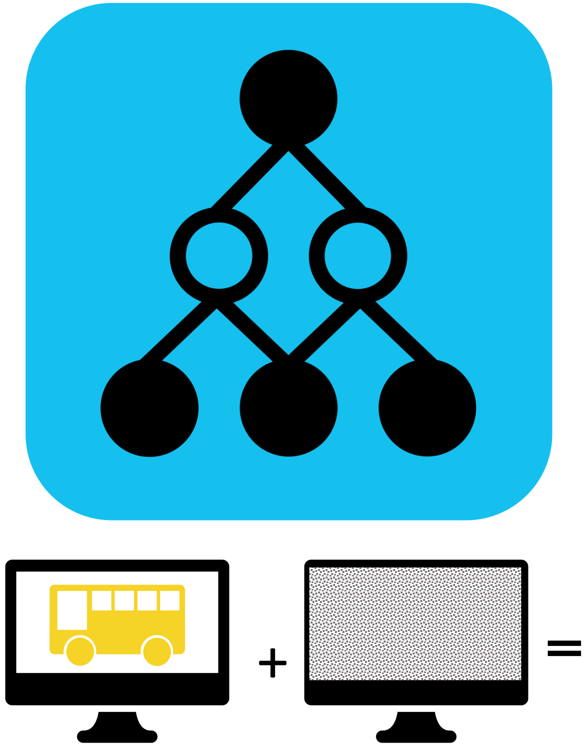
- …can get good/bad
- black box…
- …but can arbitrarily probe and get a label
- label = malicious / benign
- also a viable solution for traditional AV scanners

MalGan [PE: known features] (Hu, Tan, 2017)

difficulty for adversary to bypass

Related Work: full access to model

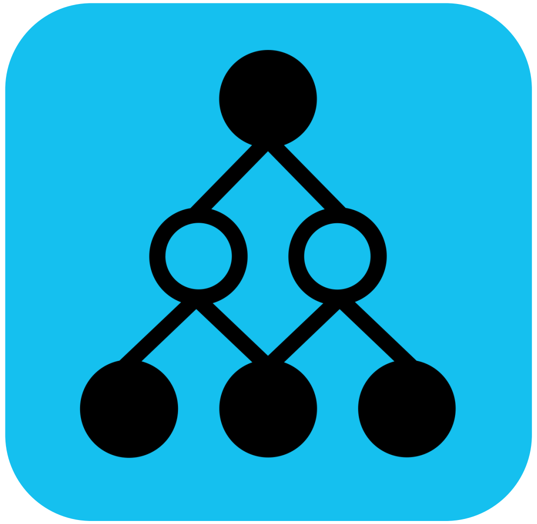
Bus (99%), Ostrich (1%)



= image

BUT…

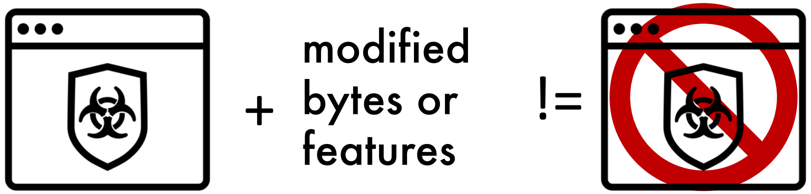
Malware (90%), Benign (10%)



Attack:

Query deep learning model:
What change will be most dramatic reduction in score?
(gradient)

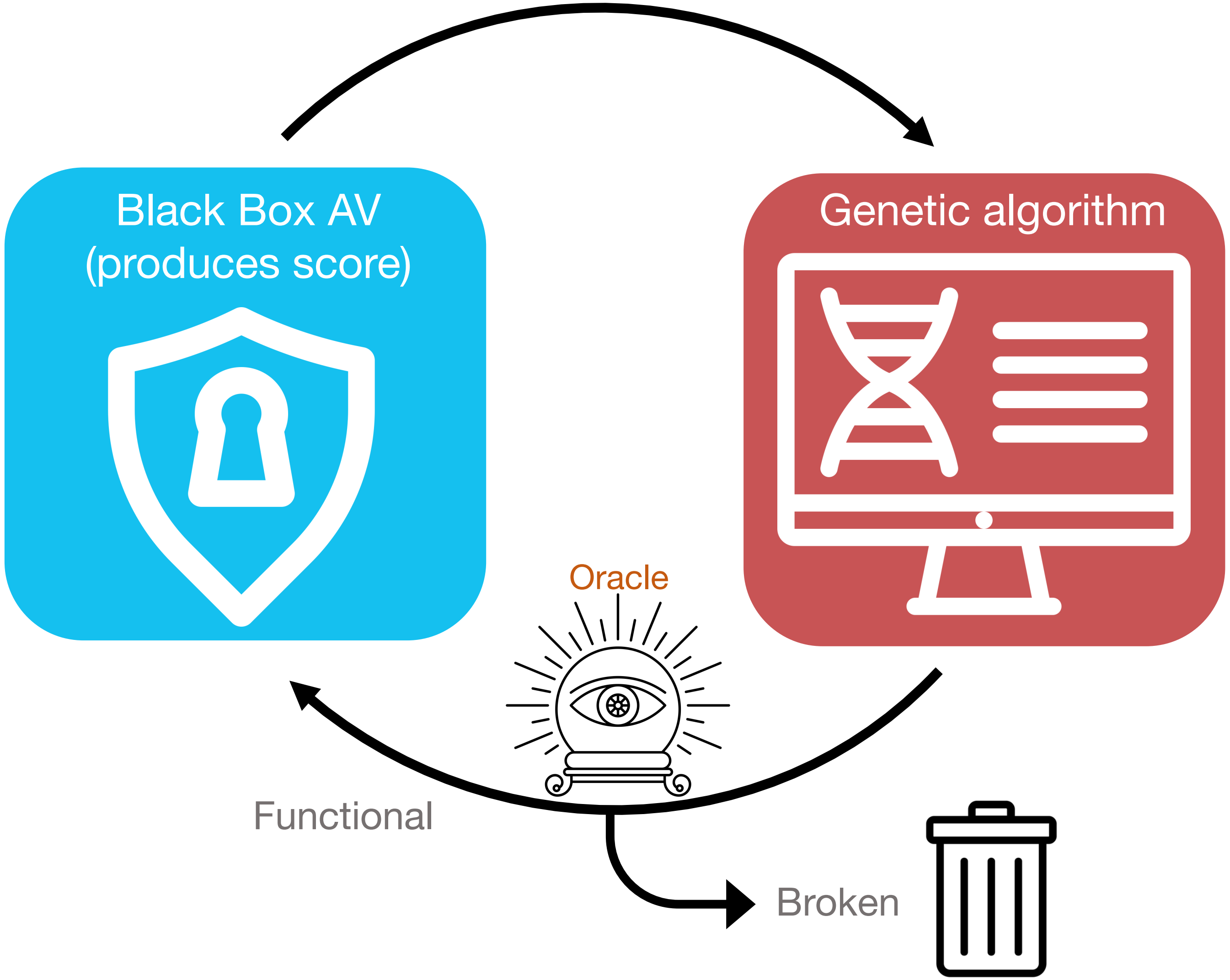
Malware variant not a PE file
Change in file breaks behavior



break PE format
destroy function

Same conditions exist for approaches based on generative adversarial networks

Related Work: attack score-reporter



Attack:
Mutate malware with benign structure to bypass AV

Mutations may break behavior

Kill strains that break format or change behavior (sandbox; expensive)

EvadeML [for PDF malware]
(Xu, Qi, Evans, 2016)

Summary of Previous Works

Gradient-based attacks: perturbation or GAN

- Attacker requires full knowledge of model structure and weights
    - Or can train a mimic model
- Presents worst-case attack to the model
- Generated sample may not be valid PE file

Genetic Algorithms

- Requires only score from black box model
- Oracle/sandbox [expensive] needed to ensure that functionality is preserved

Goal: Design an AI that chooses format- and function-preserving mutations to bypass black-box machine learning.   Reinforcement Learning!

Atari Breakout

Nolan Bushnell, Steve Wozniak, Steve Bristow

Inspired by Atari Pong

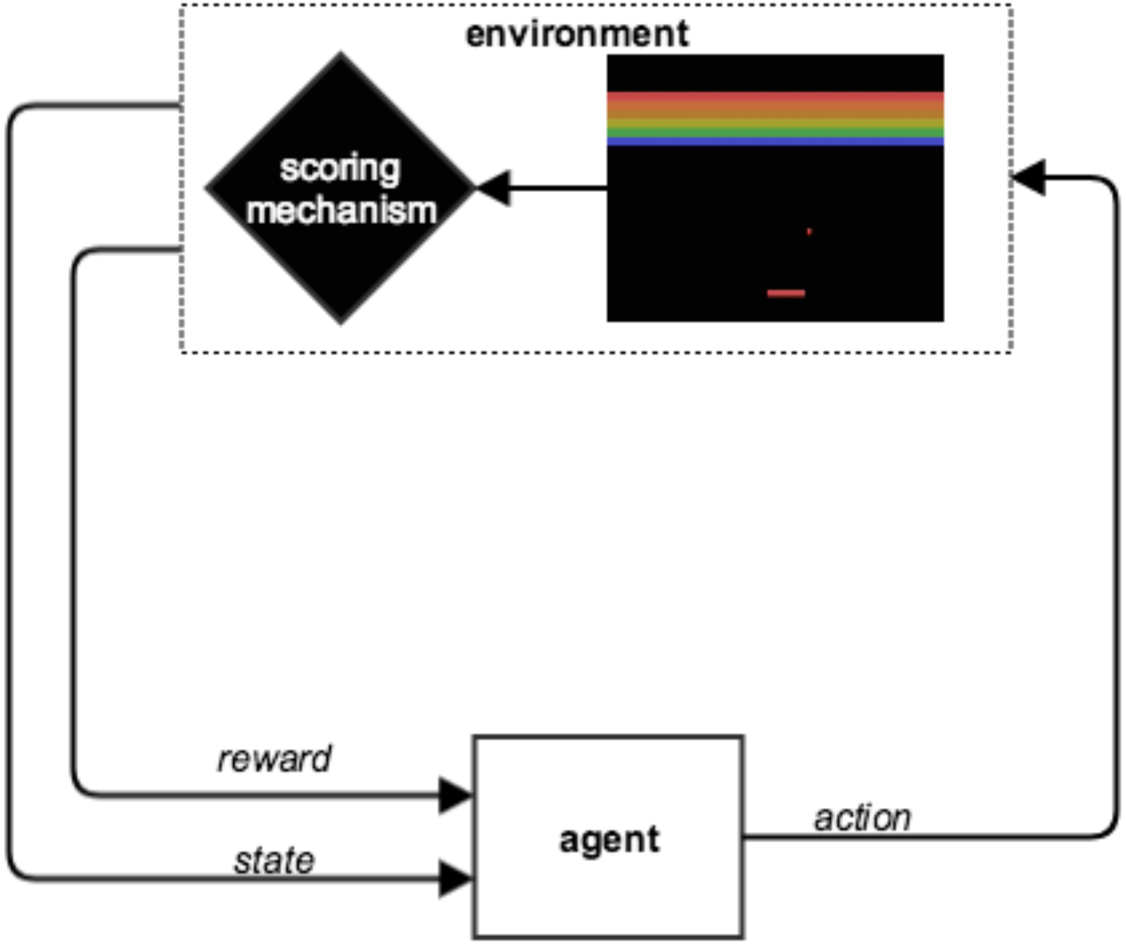
"A lot of features of the Apple II went in because I had designed Breakout for Atari"

(The Woz)

Game

- Bouncing ball + rows of bricks
- Manipulate paddle (left, right)
- Reward for eliminating each brick

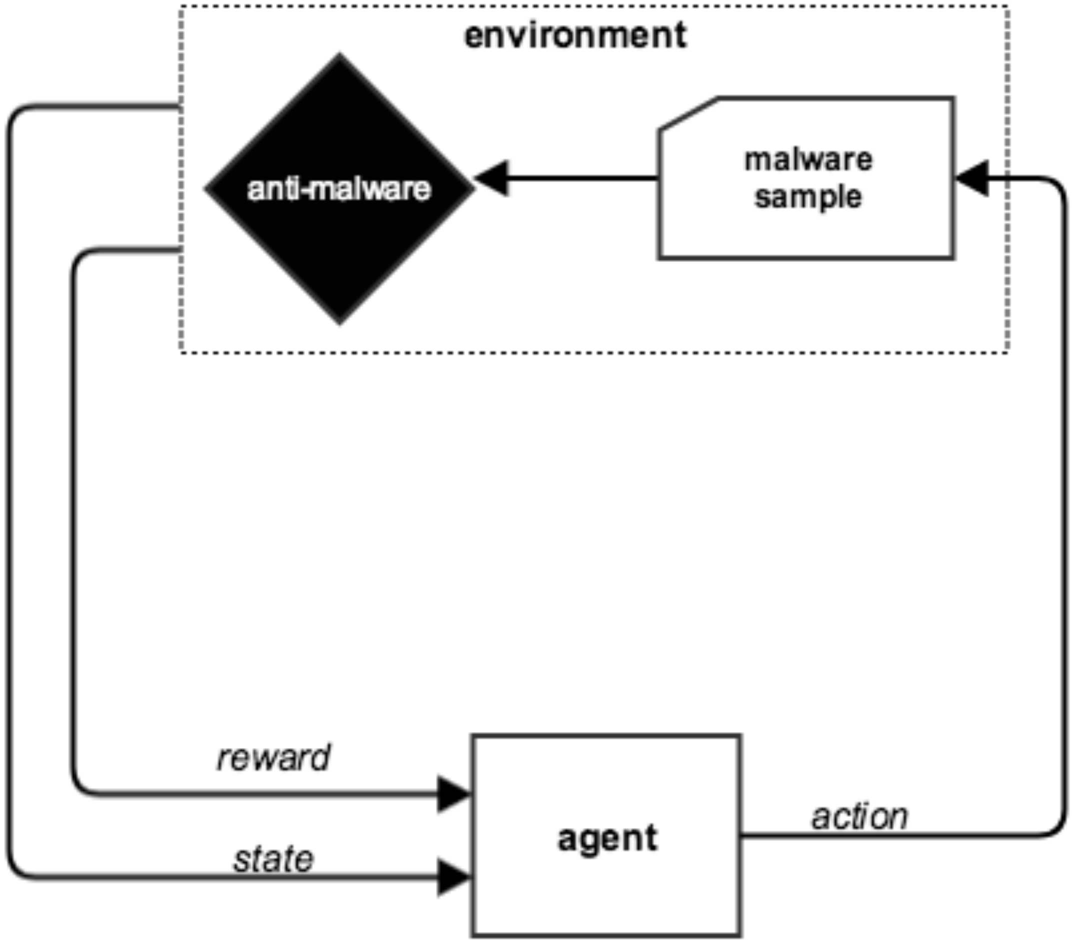
Atari Breakout: an AI



- **Environment**
  - Bouncing ball + rows of bricks
  - Manipulate paddle (*left, right*)
  - Reward for eliminating each brick
- **Agent**
  - Input: **environment state** (*pixels*)
  - Output: **action** (*left, right*)
  - Feedback: delayed **reward** (*score*)
- Agent learns through 1000s of games what action to take given state of the environment

https://gym.openai.com/envs/Breakout-v0

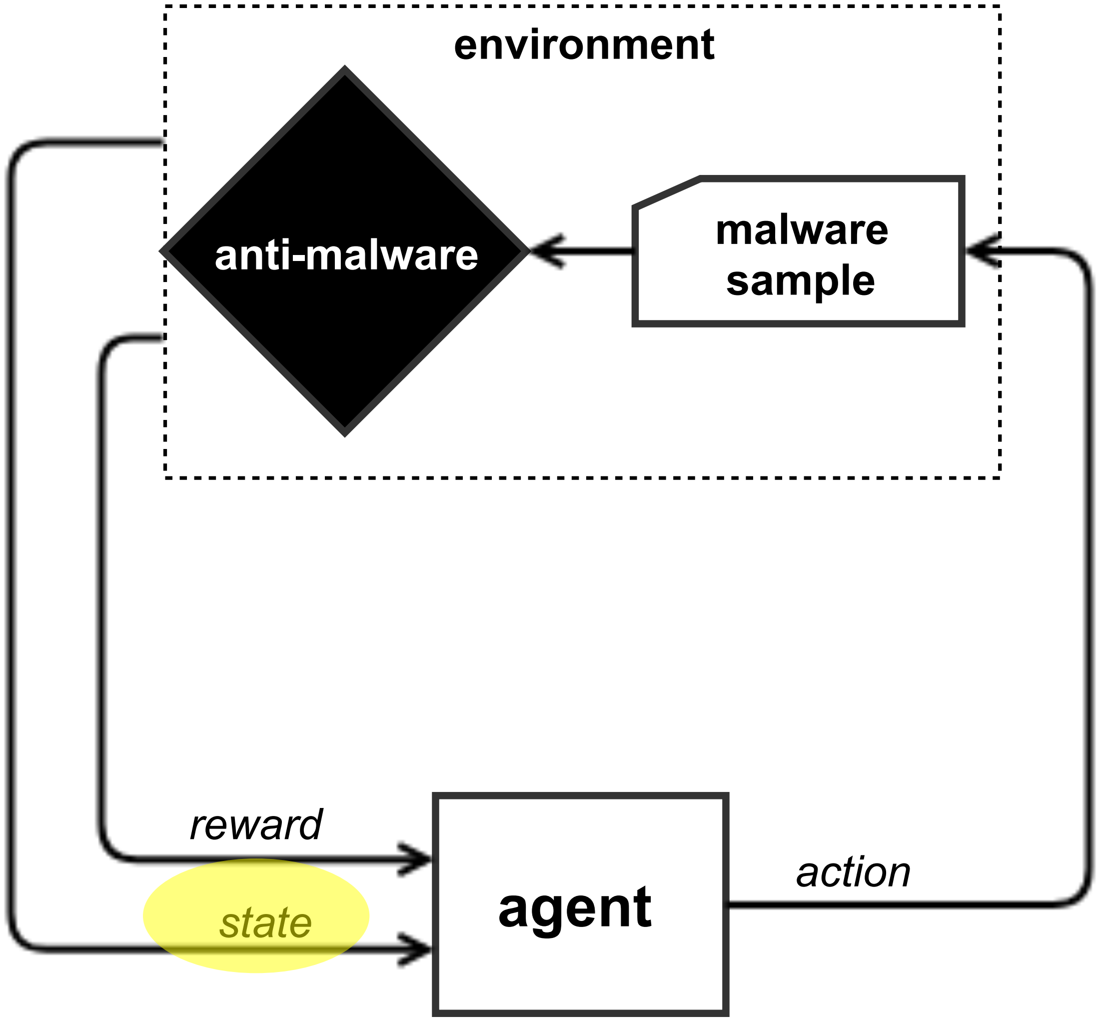
Anti-malware evasion: an AI



- **Environment**
  - A malware sample (*Windows PE*)
  - Buffet of malware mutations
    - *preserve format & functionality*
  - Reward from static malware classifier

- **Agent**
  - Input: **environment state** (*malware bytes*)
  - Output: **action** (*stochastic*)
  - Feedback: **reward** (*AV reports benign*)

The Agent's State Observation

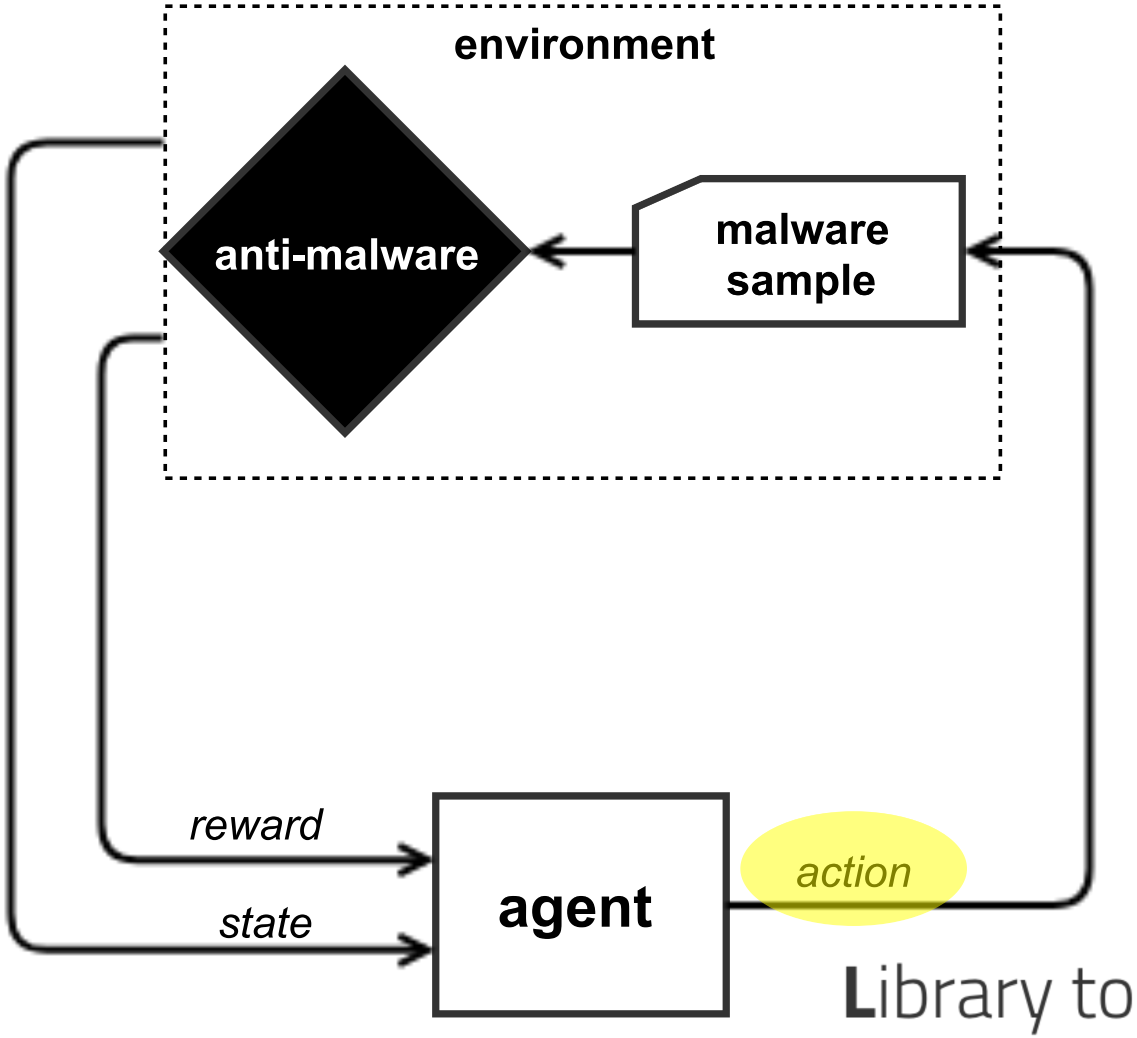


Features

- Static Windows PE file features compressed to 2350 dimensions
  - General File Information
  - Machine/OS/linker info
  - Section characteristics
  - Imported/exported functions
  - Strings
  - File byte and entropy histograms

- Fed to neural network to choose choose the best action for the given "state" (Deep Q-Learning)

The Agent's Manipulation Arsenal



environment

anti-malware

malware sample

reward

state

agent

action

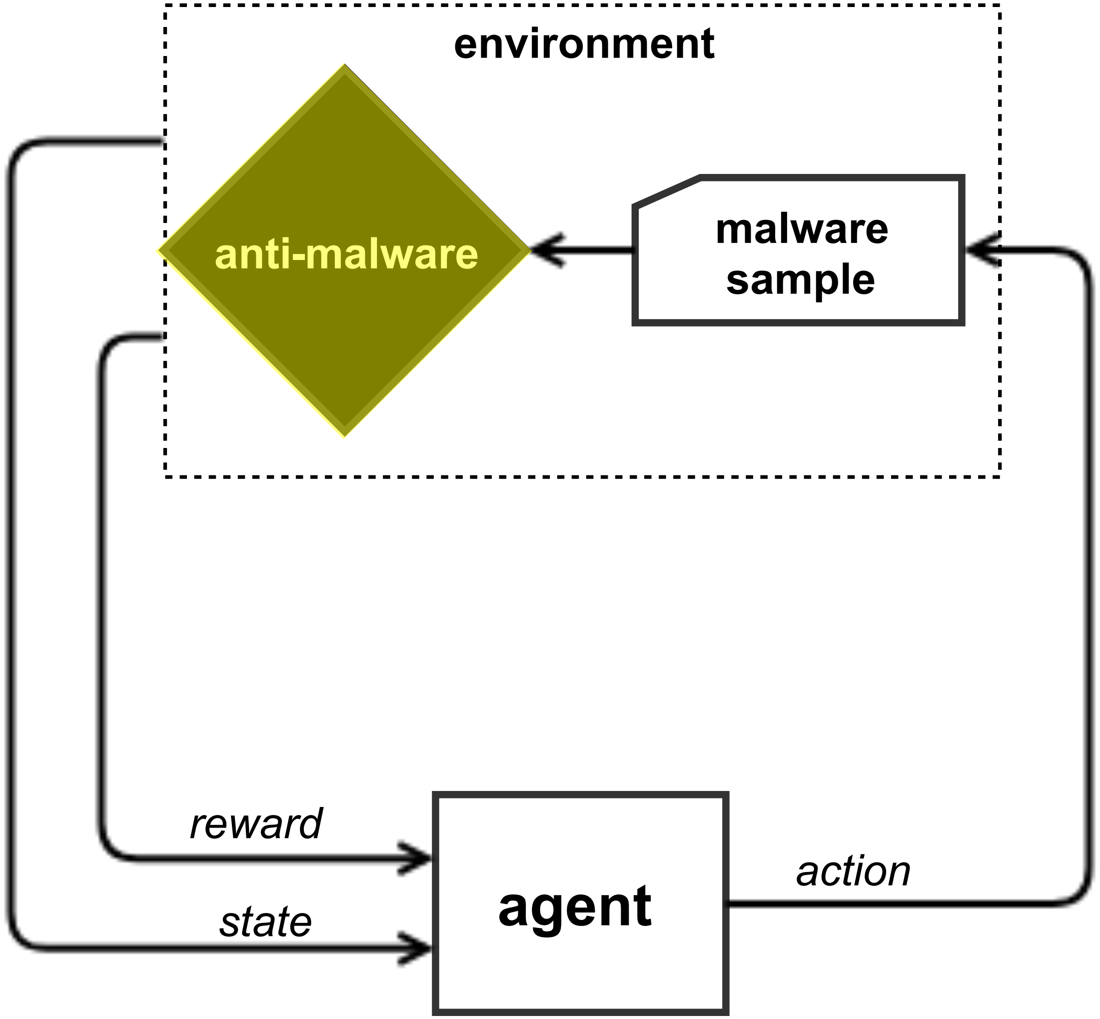
Functionality-preserving mutations:

- **Create**
  - New Entry Point (w/ trampoline)
  - New Sections
- **Add**
  - Random Imports
  - Random bytes to PE overlay
  - Bytes to end of section
- **Modify**
  - Random sections to common name
  - (break) signature
  - Debug info
  - UPX pack / unpack
  - Header checksum
  - Signature

Quarkslab

Library to **I**nstrument **E**xecutable **F**ormats

The Machine Learning Model



Static PE malware classifier

- gradient boosted decision tree (*non-differentiable*)
- need not be known to the attacker
- for demo purposes, we reuse feature extractor employed by the agent to represent "state"
- present an optimistic situation for the agent

Machine learning malware model (w/ source!) for demo purposes only. Resemblance to Endgame or other vendor models is incidental.

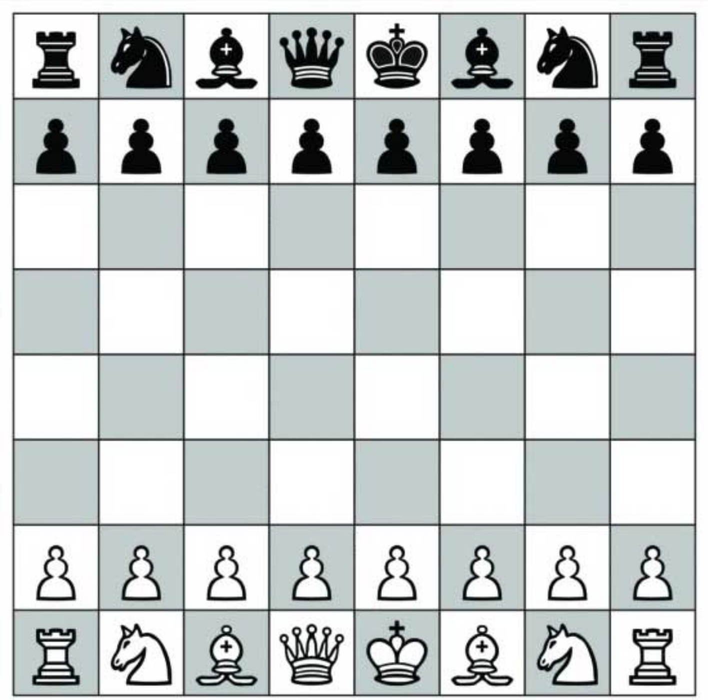
Game Setup

Environment

- No concept of "*you lose, game over*"
  - artificially terminate game after max_turns unless unsuccessful
- GBDT Model trained on 100K benign+malicious samples

Agent

- *Agent #1*: gets score from machine learning malware detector
- *Agent #2*: gets malicious/benign label
- Double DQN with dueling network with replay memory

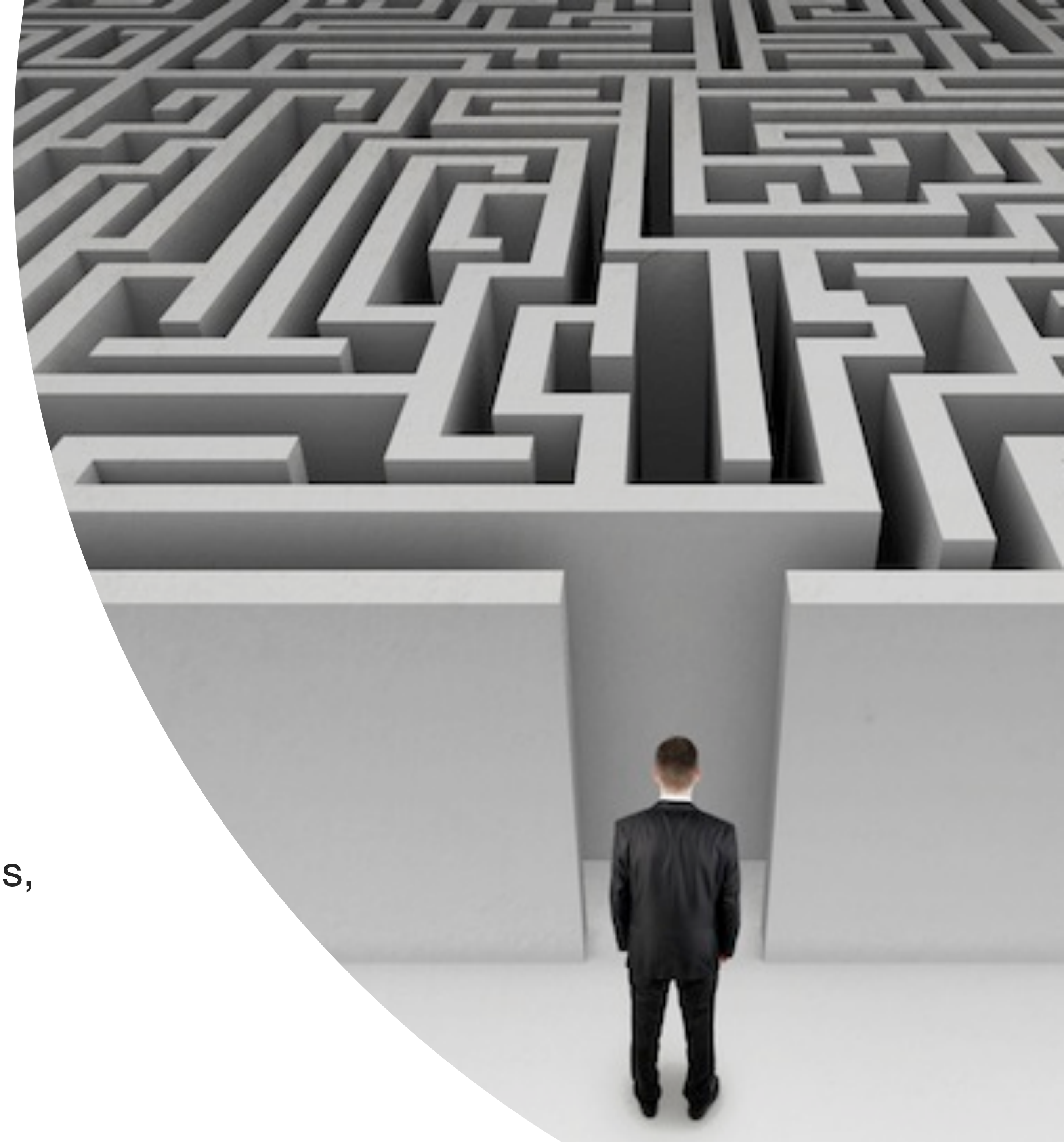


Shall we play a game?

Expectation Management

- Agent has no knowledge about AV model (*black box*)
- Agent receives incomplete
- Agent has limited (and stochastic) actions

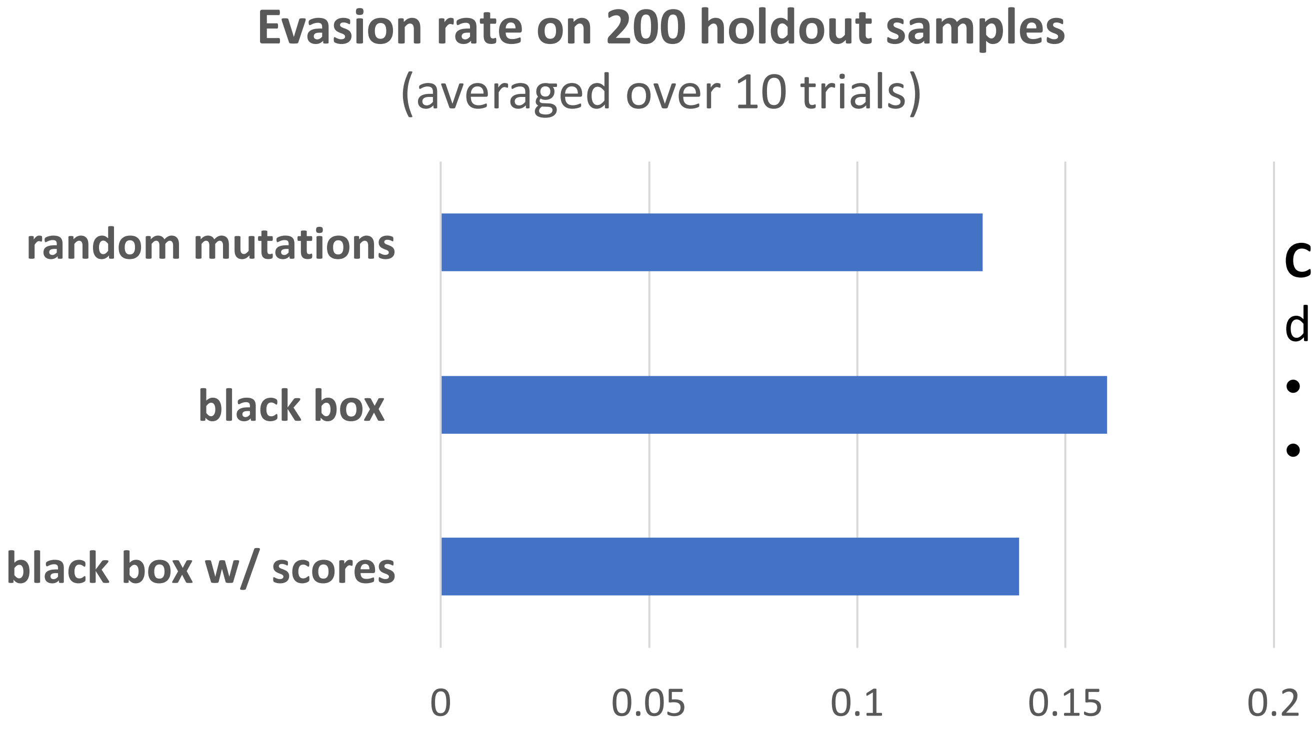
…but AV engines conservative to prevent FPs, so maybe there's a chance…



Ready, Fight!

Evasion Results

15 hours to do 100K trials (~10K episodes x 10 turns each)



Cross-evasion: on average, detection rate on VirusTotal drops

- from 35/62 (original)
- to 25/62 (evade)

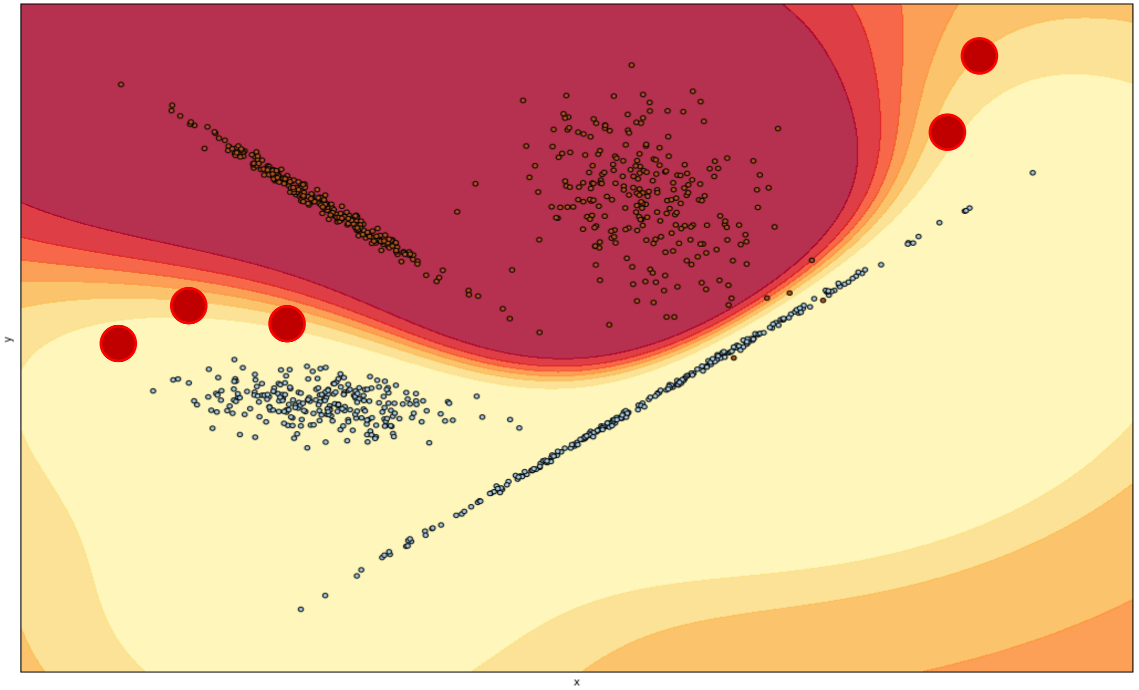
Warning Long episodes can "*overattack*" to specific model

add_section, add_section, add_section, add_section, add_section

Model Hardening Strategies

Adversarial training

- Train with new evasive variants



Feedback to the human

category	evasion %	dominant action sequence
ransomware	3%	unpack->add section->change entrypoint
backdoor	1%	pack (low entropy)->add imports

We're releasing code

gym-malware **OpenAI** environment

https://github.com/drhyrum/gym-malware

Agent

- Preliminary DQN agent for playing game
- [**contribute**] improve actions, improve RL agent

Environment

- [**provided**] Manipulations written via LIEF to change elements of a PE file
- [**provided**] Feature extraction via LIEF to convert raw bytez into environment "state"
- [**you provide**] API access to AV engine you wish to bypass (default: attack toy mode that is provided)
- [**you provide**] Malware samples for training and test

Summary

- Machine Learning Models quite effective at new samples
    - But all models have blind spots that can be exploited

- Our ambitious approach
    - Craft a game of bot vs. AV engine
    - Variants guaranteed to preserve **format** and **function** of original
    - Manipulates binaries: no malware source code needed
    - No knowledge of target model needed

- Only modest results. Make it better!
  https://github.com/drhyrum/gym-malware

Thank you!

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