

Machine Learning for Defensive Cybersecurity

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 - Sequential ML for network security
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Current state of security

Microsoft downplays threat from SolarWinds attackers according to new report

John Leyden 04 January 2021 at 14:49 UTC
Updated: 04 January 2021 at 14:55 UTC

Cyber-attacks Microsoft Data Breach

Software blueprints acquired but not altered

Total malware

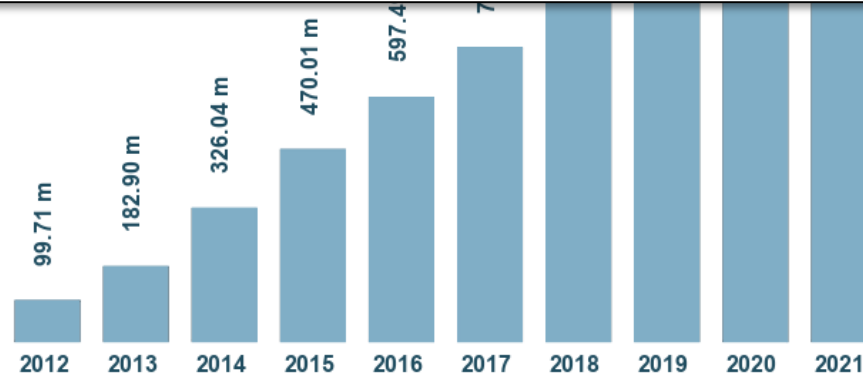
AVTEST

Researchers among clean hacking campaign



Looking for zero-day browser and OS

Machine learning can help!

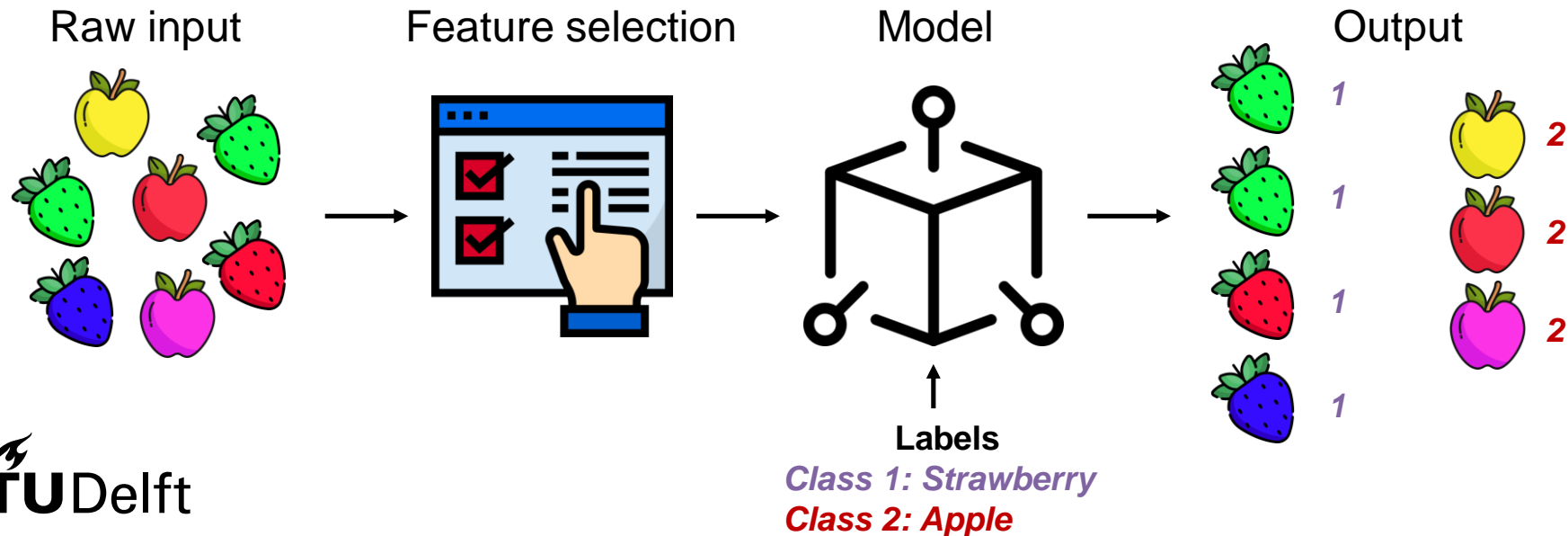


Last update: January 27, 2021

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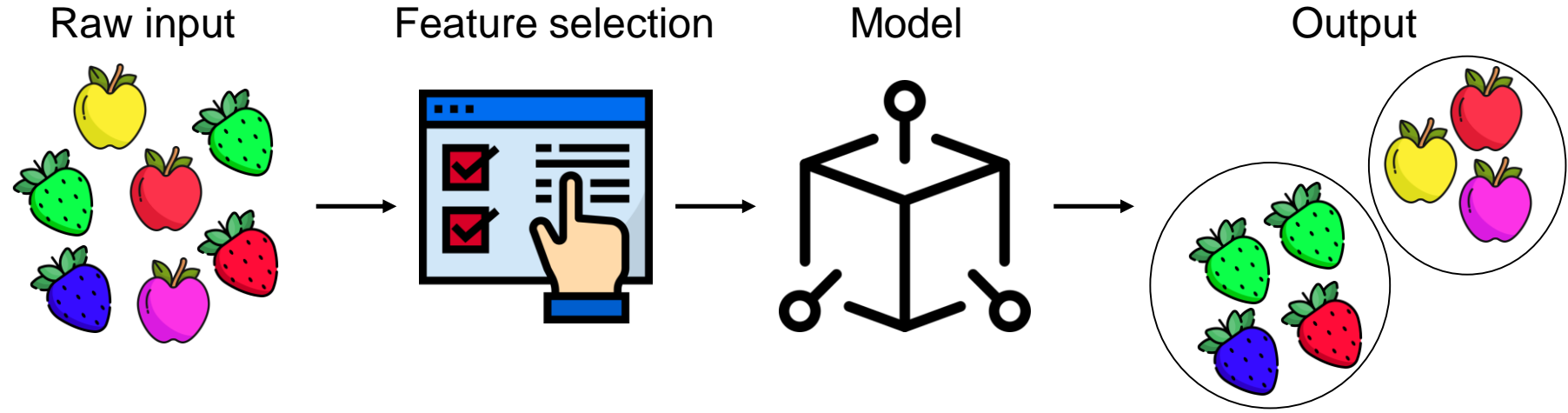
Machine learning

- Learn patterns from input data
- Under the hood: *Optimize an objective function*



Machine learning

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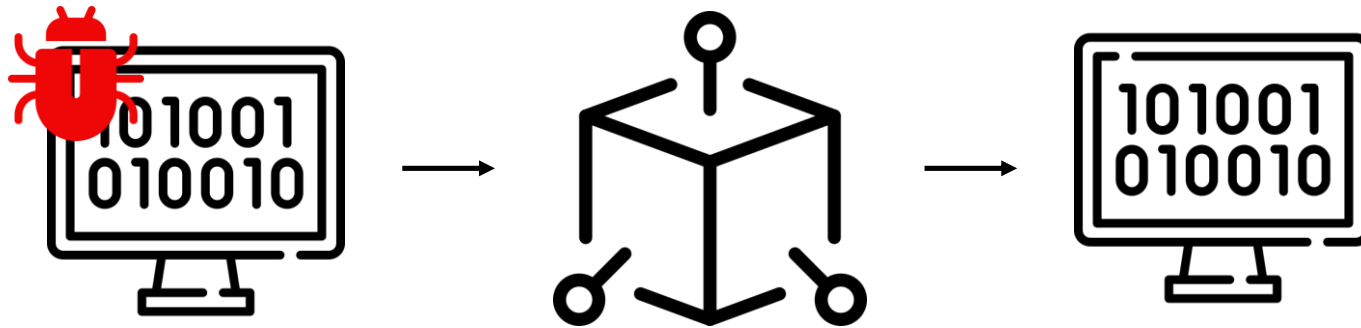


ML for defensive cybersecurity

- Spam detection
- Malware detection
- Detect and patch buggy code
- Detect real-time attacks
- Profile attacker behavior
- Anomaly detection
- Attacker modelling
 - APT modelling
- ...
- *Offensive security applications*
 - *Crafting malware, hardware attacks, ...*

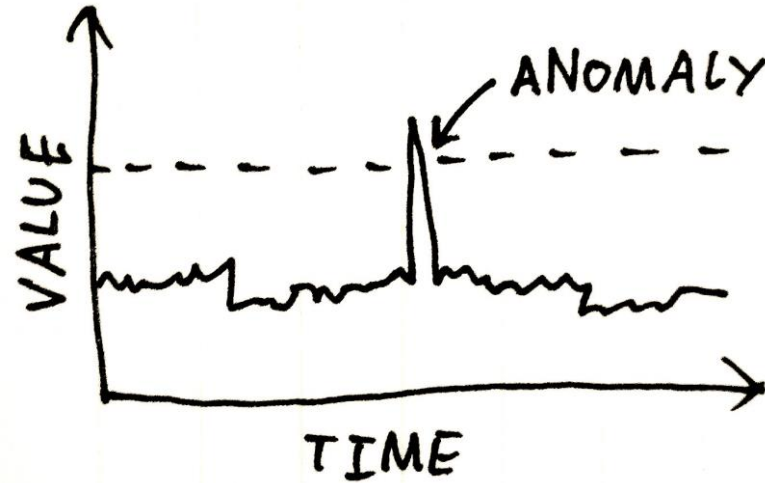
ML for defensive cybersecurity

- Detect and patch buggy code



ML for defensive cybersecurity

- Anomaly detection



ML for defensive cybersecurity

- Malware detection → Predicting impending exposure



ML for defensive cybersecurity

- Malware detection → Capability assessment

Behavior profile



- Connects with C&C
- Opens backdoors
- Persistent

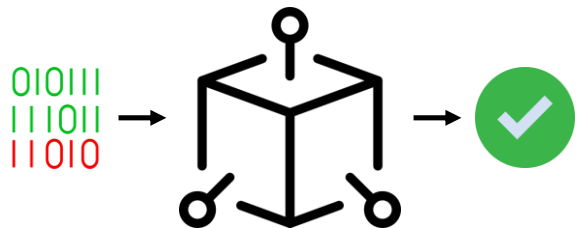
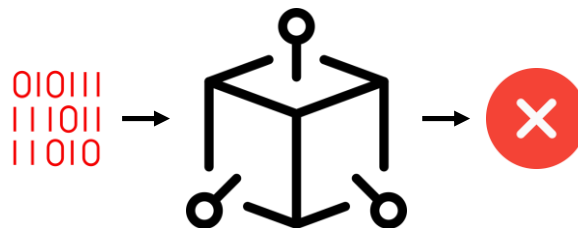
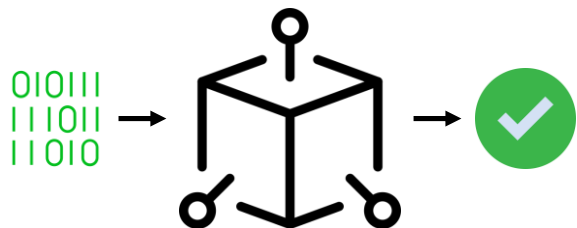
vs.

Label

Zeus

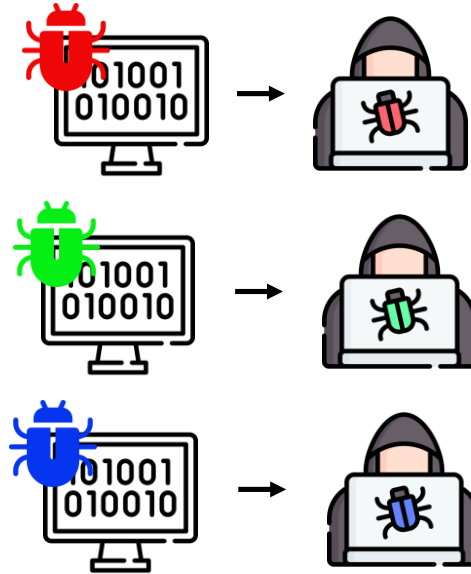
ML for defensive cybersecurity

- Malware detection → Adversarial ML



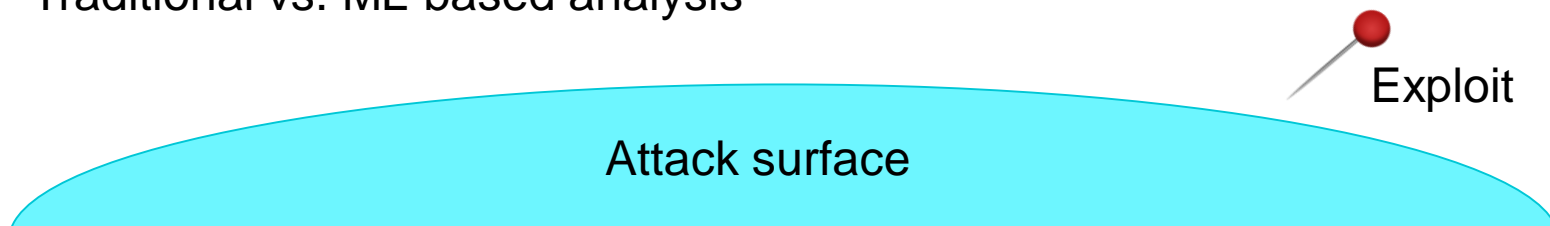
ML for defensive cybersecurity

- Malware detection → Author attribution



Industry perspective

- Divide between academia & industry
- ML's slow adaptation
 - Traditional vs. ML-based analysis

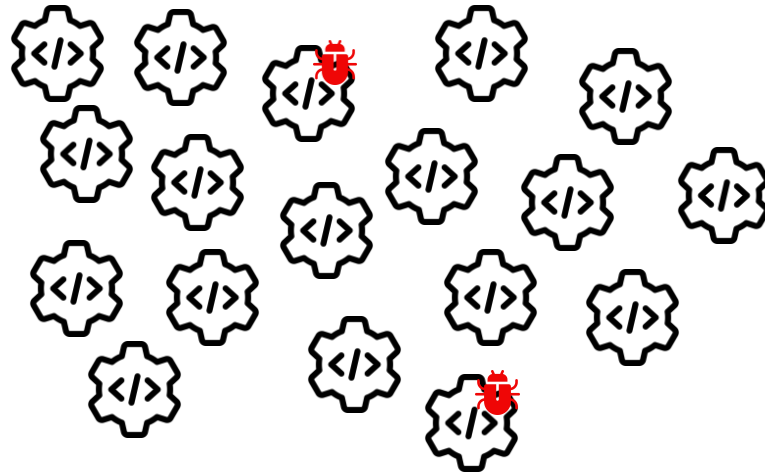


ML is not a silver bullet

- Cannot blindly apply ML to Security
 - Address unique problems
- Do not throw data in black-box
 - Ethical considerations

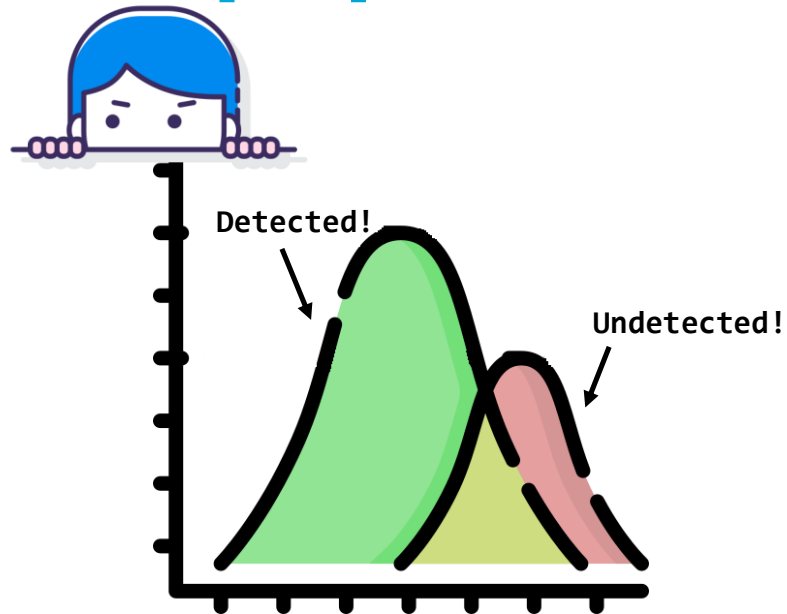
(Caution!) More goodware than malware [1/4]

- Security data has class imbalance
- Unrealistic class distribution
 - Bias in data → bias in models
- Use real class distribution
- Use imbalance-aware algorithms



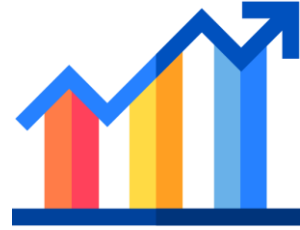
(Caution!) Landscape is adversarial [2/4]

- Attackers hide, malware evades detection
- ML cannot detect all evasion attempts!
- Representative dataset is required!
- ML can adapt to changing landscape
 - Trigger re-learning



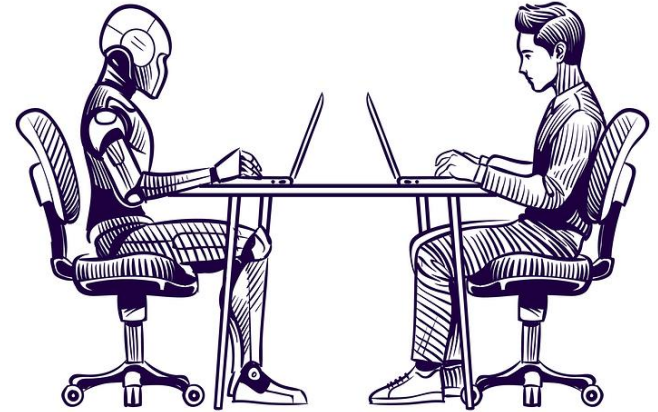
(Caution!) Know what to evaluate [3/4]

- Be mindful of evaluation metrics
 - Precision, Recall, AUC, F1 score ...
 - Accuracy in imbalanced datasets
- Performance metrics \neq improved security
- Better understanding fosters better models
 - Prediction vs. understandability



(Caution!) Know the limitations of ML [4/4]

- Can find patterns faster than humans
 - But is also really stupid
- Cannot replace human intelligence
 - Trade-off between automation and explainability
- Build human-in-the-loop ML pipelines



Take-aways

- ML enables human analysts to do complex tasks
 - A powerful technology for defensive security
 - But cannot blindly apply it
- ML used for both defense and offense
 - Performance metrics \neq security
 - Robust classifiers required
- ML is not a silver bullet for all security problems
 - Explainable and Human-in-the-loop ML is paramount

Thank you!



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