

# The Challenge

NATHAN HAMIEL SENIOR DIRECTOR OF RESEARCH Applied Resea <sup>-</sup>undamenta



- Different perspectives and priorities
- Responsibilities not defined
- Legacy processes and tooling
- Lack of AI knowledge on the security team
- Messy and complex world



- Governance not implemented
- Model implementations are highly specific
- Regulatory requirements
- Improper project definitions
- Lack of appropriate benchmarks





Nathan Hamiel SENIOR DIRECTOR OF RESEARCH Security of Emerging Technologies International Public Speaker Black Hat Review Board Member Track Lead: AI, ML, and Data Science



https://kudelskisecurity.com





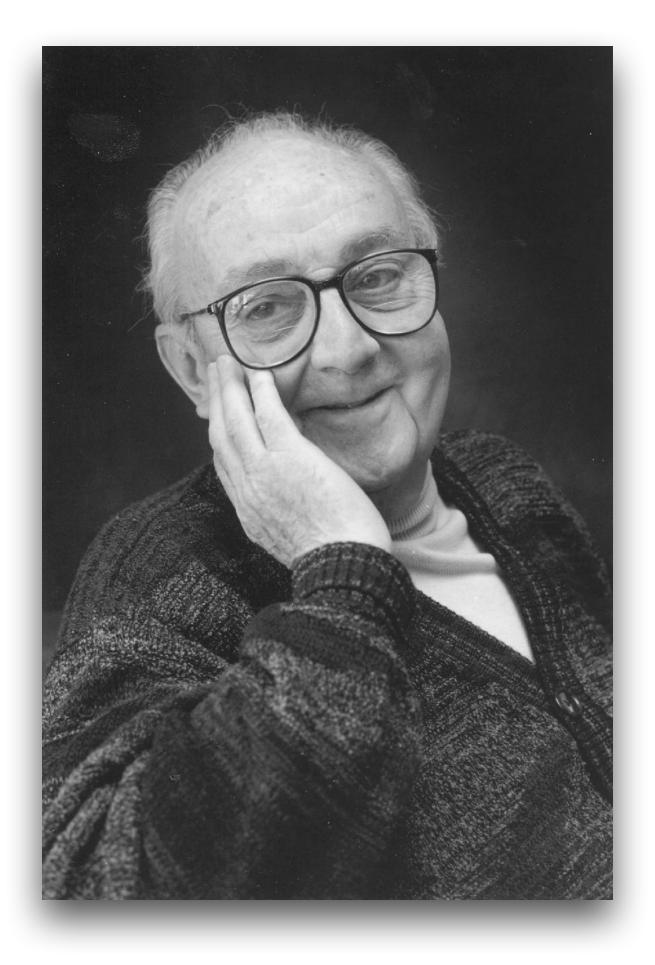


### "All models are wrong, but some are useful."

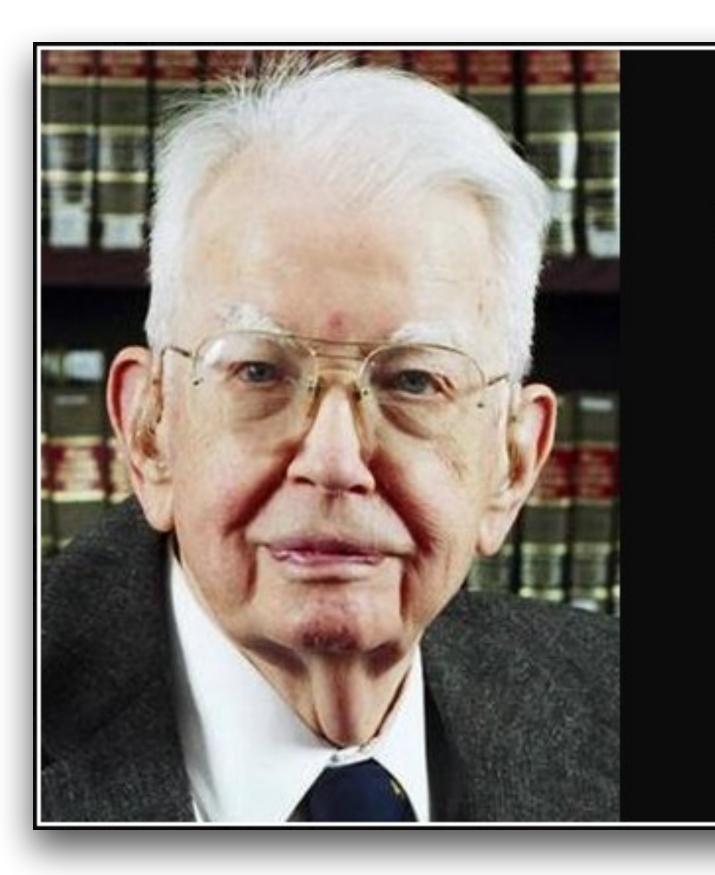
-George Box













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### If you torture the data long enough, it will confess.

- Ronald Coase -

AZQUOTES









### The Real World Is Messy







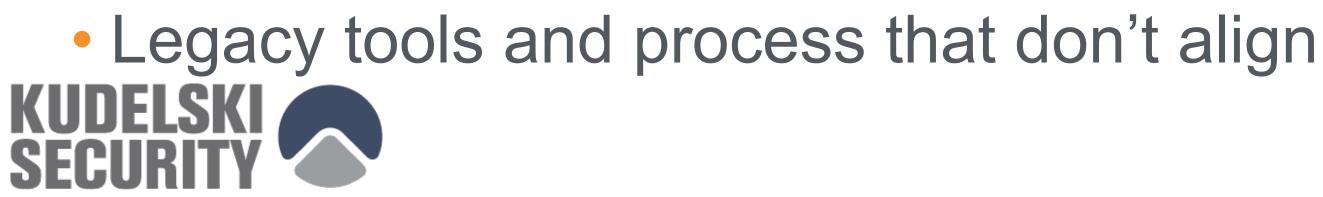
## Al Risk and Challenges

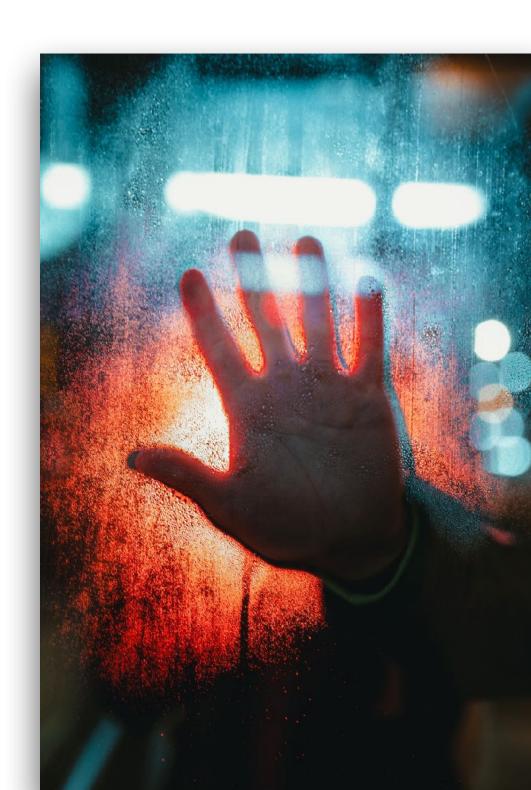




# What Makes Al Risky?

- Poorly defined problem / Goals
- Lack of explicit programming logic
- Data
- Lack of visibility and explainability in some approaches
- Uncertainty
- Lack of appropriate benchmarks
- Concept Drift and Data Drift







# What Bad AI Really Looks Like

TOM SIMONITE

BUSINESS 07.10.2020 07:00 AM

### Meet the Secret Algorithm That's Keeping Students Out of College

The International Baccalaureate program canceled its high-stakes exam because of Covid-19. The formula it used to "predict" scores puzzles students and teachers.

### What Happens When Computer Programs **Automatically Cut Benefits That Disabled People Rely on to Survive**

HEADLINE OCT 16, 2020

October 21, 2020 / Lydia X. Z. Brown

### Why some onions were too sexy for Facebook

() 8 October





First death in a self-driving car happens in a Tesla

JUNE 30, 2016 / 6:29 PM / AP

# experience

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> University of Miami Reportedly Used Facial **Recognition to Discipline Student Protesters**

Al Camera Ruins Soccer Game For Fans After Mistaking **Referee's Bald Head For Ball** 



minorities

Lee Luda, built to emulate a 20-year-old Korean university student, engaged in homophobic slurs on social media

Man wrongfully arrested due to facial recognition software talks about 'humiliating'



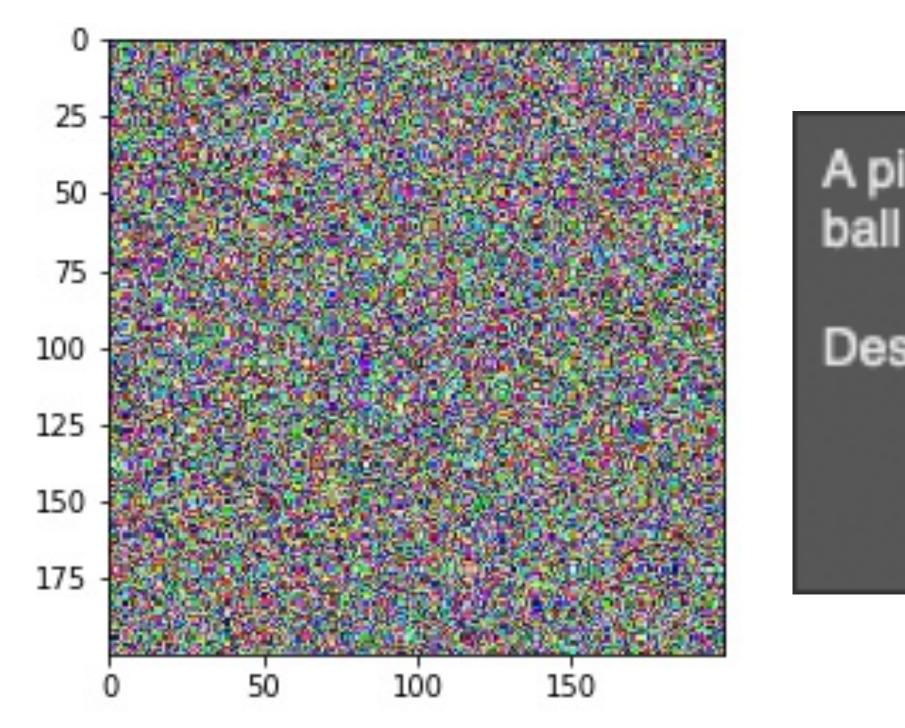


루다랑 친구하기 🕅









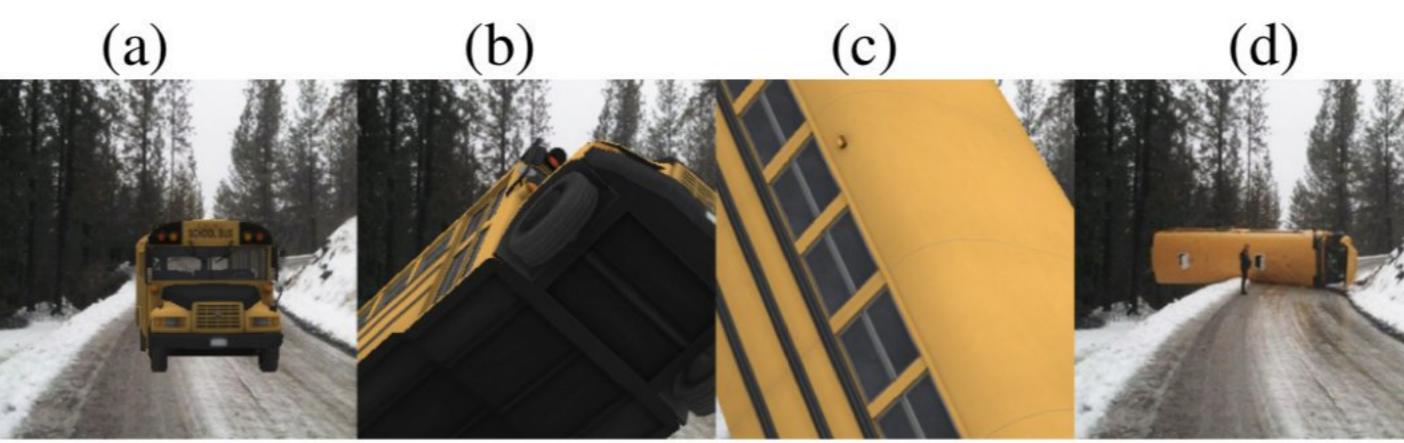
https://research.kudelskisecurity.com/2020/07/23/fooling-neural-networks-with-noise/



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# A picture containing elephant, people, large, ball

Description automatically generated





motor scooter 0.99 parachute 1.0



Alcorn, et al., 2019



fire truck 0.99 school bus 0.98

Fragility

## Cutting Edge Attacks!!!

bobsled 1.0

parachute 0.54

fireboat 0.98

bobsled 0.79



Fundamental and Applied Researc

# Health and Safety

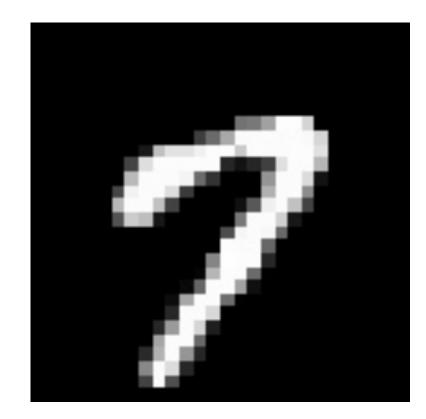


https://research.kudelskisecurity.com/2020/07/23/fooling-neural-networks-with-rotation/



	Network	Classification	Score
	vgg16	cannon	0.3462
	resnet18	tractor	0.2012
	alexnet	tank	0.4665
	densenet	thresher	0.1893
	Inception	motor_scooter	0.5318

# Model Backdoors

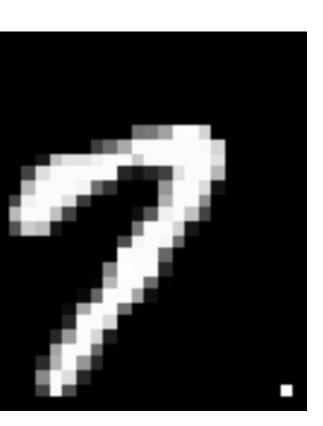


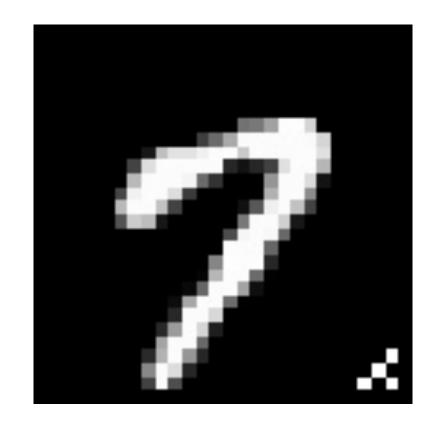
**Original Image** Gu, et al., 2019





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### Pattern Backdoor

# Supply Chain Issues

- You could inherit all of the issues of the previous model
- Attackers can exploit lack of visibility
- Model sharing and reuse is encouraged
  - How do you know when there is a problem
  - How do updates happen
- Use trusted sources

https://research.kudelskisecurity.com/2020/10/29/building-a-simple-neural-network-backdoor/





Fundamental and Applied Research

# **Risk Perspectives and Confusion**

- 65% of respondents's companies can't explain how decisions or predictions are made
- 73% have struggled to get executive support for prioritizing AI ethics and Responsible AI practices

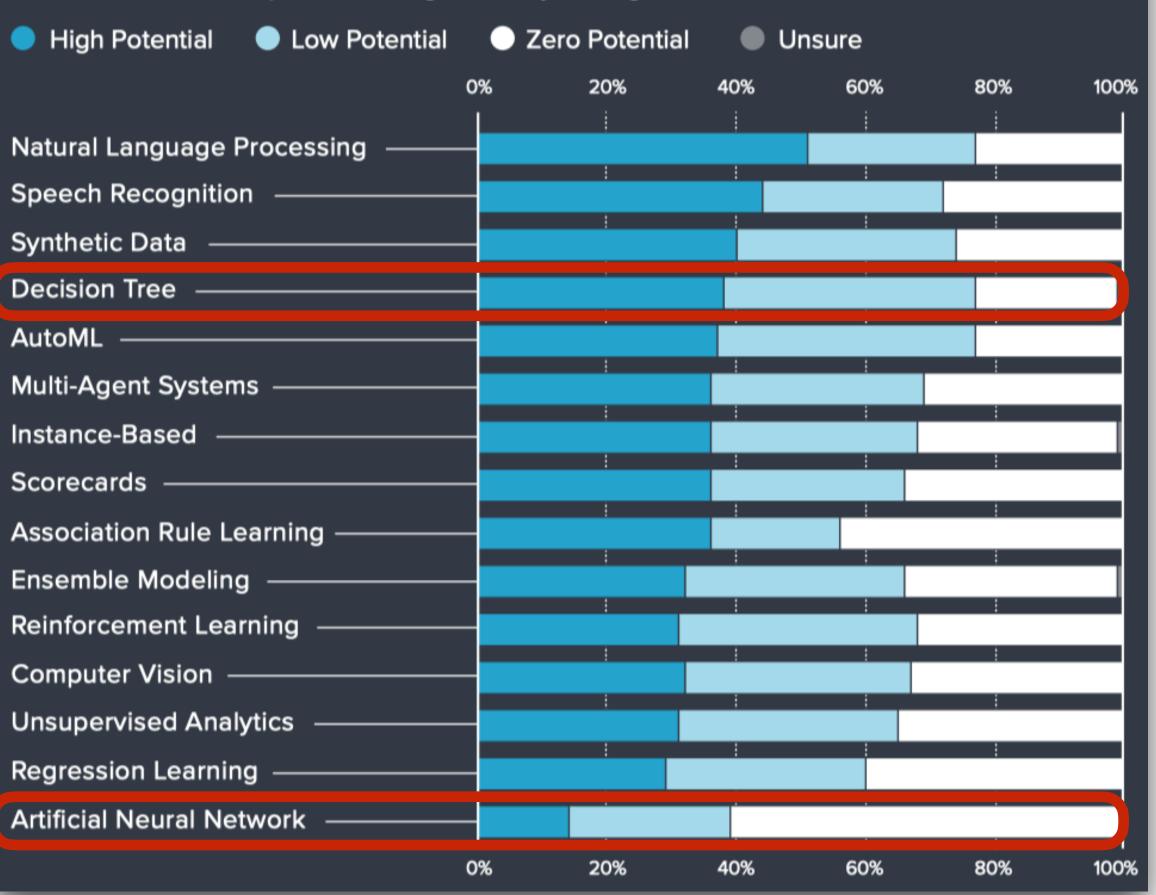
The State of Responsible AI: 2021

https://www.fico.com/en/latest-thinking/market-research/state-responsible-ai-2021



### All Model Types are Showing Potential for Misuse

What model types are showing the greatest risk for potentially unethical and/or irresponsible usage within your organization?



# Security

- We live in an increasingly customized and specific world
- There isn't a typical attacker process or kill chain to interrupt
- Security is often misaligned and out of the loop
- Security lacks expertise in the AI/ML area
  - We need to ensure that threats are identified during the development lifecycle and risk mitigated to acceptable levels
  - We apply proper testing to systems



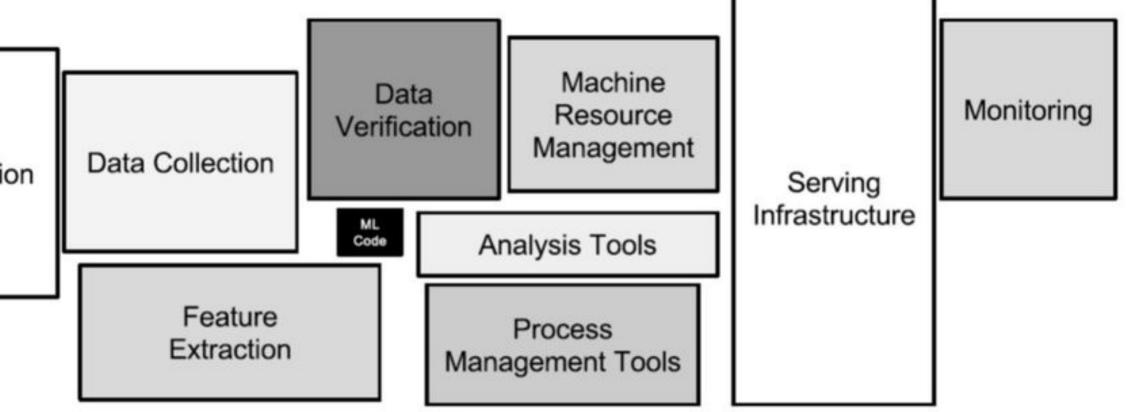


### Attack Surface

- Model
- Processes
- Hosting infrastructure
- Training data

Configuration





Sculley, et al., 2015

### Attacks

- Traditional Platforms
  - Applications, Cloud, IoT, Sensors, etc.
- Some ML Specific Attacks
  - Model Evasion
  - Model Poisoning
  - Membership Inference
  - Model Theft / Functional Extraction









### Inventory





### Deconstruct

### Recommend

### Assess

# Quick Risk Eval

- What does the system do?
- Does it support a critical business process?
- Was it trained on sensitive data?
- How exposed is it going to be?
- What would happen if the system failed?
- Could the system be misused?
- Does it fall under any regulatory compliance?



# Security Testing

- Spin up
- Encompass traditional and model specific approaches
- Define a goal and think like an attacker
- ML attacks are situational

  - Observe outputs
  - Repeat

• A little coding, a little skill, and a little luck KUDELSKI SECURITY

### Manipulate features and modify inputs based on ML approach

### **Evaluate Attacks and Defenses**

- More attacks and proposed defenses are coming
- Build a way to evaluate both attacks and defenses
  - Separate security testing pipeline
  - Integrate tooling
  - Evaluate effectiveness and impact



### **Be Careful**

- Choices to use or not use a control should be purposeful
  - Robustness training
- - Fully homomorphic encryption
  - Defensive distillation
  - Feature squeezing
- Start with the basics and move on if necessary



Many recommendations may affect performance and accuracy



- Failure Modes in Machine Learning

  - https://docs.microsoft.com/en-us/security/engineering/threat-modeling-aiml
- Adversarial Threat Matrix
  - <u>https://github.com/mitre/advmlthreatmatrix</u>
- Counterfit
  - https://github.com/Azure/counterfit/
- Adversarial Robustness Toolbox



<u>https://docs.microsoft.com/en-us/security/engineering/failure-modes-in-machine-learning</u>

https://developer.ibm.com/technologies/analytics/projects/adversarial-robustness-toolbox/



- ISO Standard (Future)
- NIST (Future)
- ENISA AI Cybersecurity Challenges
- ENISA Securing Machine Learning Algorithms
  - <u>https://www.enisa.europa.eu/publications/securing-machine-learning-algorithms</u>



### • <u>https://www.enisa.europa.eu/publications/artificial-intelligence-cybersecurity-challenges</u>

Contact

Nathan Hamiel nathan.hamiel @ kudelskisecurity.com Twitter: @nathanhamiel LinkedIn https://research.kudelskisecurity.com



