



## The Role of Artificial Intelligence in Cyberdefence

Dr. Vincent Lenders, Director Cyber-Defence Campus





## When Al beats Human Intelligence

Chess

IBM Deep Blue



Go

Google Alpha Go



2011

2019

1997



Jeopardy!

**IBM Watson** 

2016

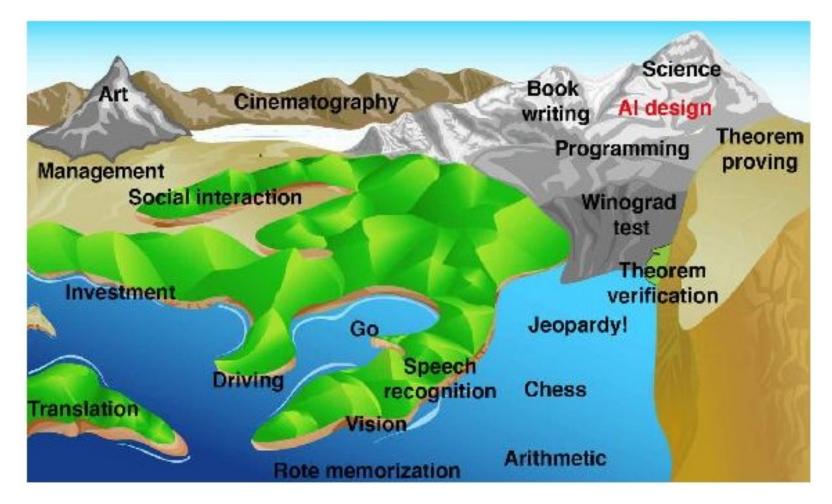


Poker

Facebook Pluribus

## **Q**

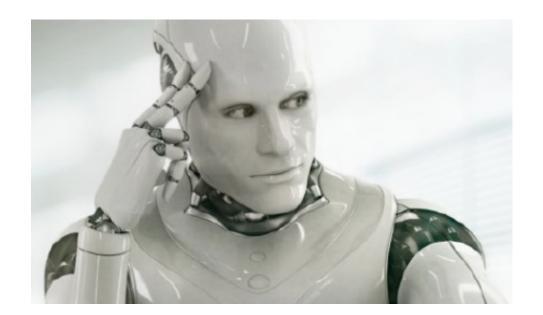
## The Uphill Path of Al Challenges



Source: Max Tegmark / Life 3.0

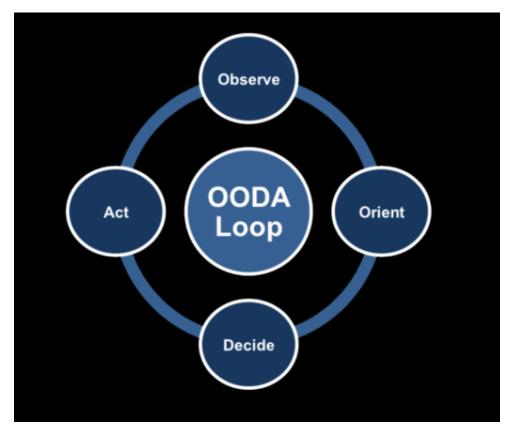


# When could **AI** beat **human** intelligence in cyberdefence?





# Cyberdefence Process The OODA Loop



Source: Lt. General Thomas Süssli, Chief of the Swiss Armed Forces CYD Campus Conference on AI, 2019



## Cyberdefence as a Game: Locked Shields



- Yearly live-fire cyberdefence exercise
- Human teams compete against each other

Teams	Role
~20 Blue Teams (BT)	Defenders
Red Team (RT)	Attacker
Green Team (GT)	Infrastructure operator
Yellow Team (YT)	Monitoring
User Simulation Team (UST)	Benign users
White Team (WT)	Organizer

Blue team with the highest score wins the game



# Towards an Al-Powered Blue Team in Locked Shields

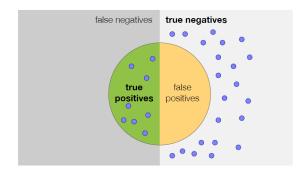


[R. Meier, A. Lavrenovs, K. Heinäaro, L. Gambazzi and V. Lenders, CyCon 21]



## **Machine Learning Use Cases**

## Detection of malicious network traffic



Continuous user authentication



Wireless signal classification





## **Detection of Malicious Network Traffic**

#### Machine learning pipeline



**Network activity** 

Feature extraction

- Flow stats
- Packet headers
- Timing

Random forest classification

#### **Locked Shields Evaluation**



#### Workflow execution, 10 cores / 16Gb RAM

Dataset		Classifier	Inference	time
	extraction	training	dataset	flow
LS17	42 min	19 min	50 s	0.110
LS18	85 min	47 min	30 s	3 µs

#### **Classifier quality**

Model	Precision	Recall
LS17-tuned	99%	98%
LS18-tuned	99%	90%

[N. Känzig, R. Meier, L. Gambazzi, V. Lenders and L. Vanbever, CyCon 19]

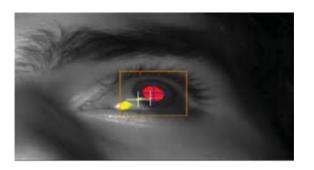


## **Machine Learning Use Cases**

#### Detection of malicious network traffic



Continuous user authentication



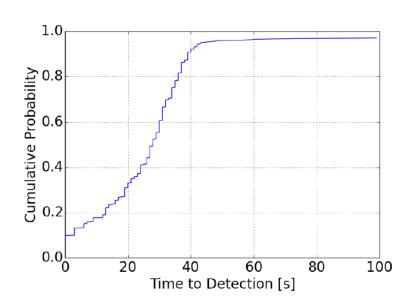
Wireless signal classification

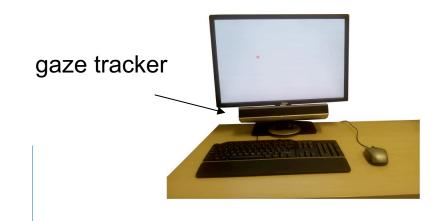


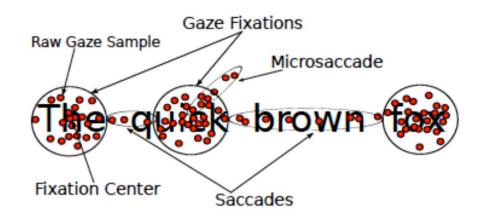


## **Continuous User Authentication**

#### authentication accuracy







[S. Eberz, K. Rasmussen, V. Lenders and I. Martinovic, ACM TOPS 15]



## **Machine Learning Use Cases**

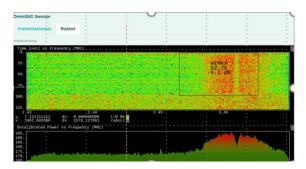
## Detection of malicious network traffic



Continuous user authentication



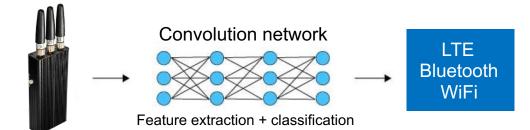
# Wireless signal classification



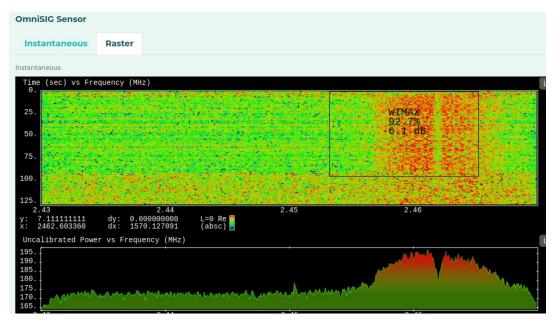


## **Wireless Signal Classification**

#### Deep learning pipeline



#### Real-time signal classification



[S Rajendran, W Meert, D Giustiniano, V Lenders, S Pollin, IEEE TCCN 18]



## Further Al Use Cases investigated at CYD Campus

#### Supervised learning

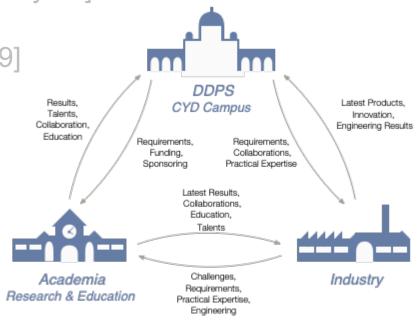
- Detection of malicious shell sessions [CyCon 19]
- Natural language understanding and machine translation [AAAI 21]
- Fake news detection
- Prediction of flight destination in aviation [OpenSky 21]

#### **Unsupervised learning**

- Wireless spectrum anomaly detection [TCCN 19]
- Mitigation of DDoS attacks
- Ranking of cyber threat feeds [CyCon 18]
- Detection of APT threats [DIMVA 17]
- Knowledge representation [arxiv 21]

#### **Reinforcement learning**

- Text generation [RanLP 21]
- Botnet detection [arxiv 21]





#### **Conclusions**

#### Pros of Al

- Al provides already today opportunities to improve cyberdefence
- Relatively easy to develop and apply new AI solutions

#### Cons of Al

- Hard to provide explainability
- Succeptible to attacks

