Siber Güvenlikte Makine Öğrenmesi

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Boğaziçi Üniversitesi DataCamp'22
13 Kasım 2022

CyBOK - The Cyber Security Body of Knowledge

The Cyber Security Body of Knowledge

1. Human, Organisational & Regulatory Aspects
2. Attacks & Defences
3. Systems Security
4. Software and Platform Security
5. Infrastructure Security

https://www.cybok.org/knowledgebase1_1

CyBOK - The Cyber Security Body of Knowledge

1. Human, Organisational & Regulatory Aspects

1. Risk Management & Governance
2. Law & Regulation
3. **Human Factors**
4. **Privacy & Online Rights**

CyBOK - The Cyber Security Body of Knowledge

2. Attacks & Defences

1. **Malware & Attack Technologies**
2. Adversarial Behaviours
3. **Security Operations & Incident Management**
4. Forensics

Challenges in AI-based Malware Detection

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2. Performance
3. Encrypted data
4. Static analysis might not be enough
5. Malware can detect that it is inside a virtual machine

CyBOK - The Cyber Security Body of Knowledge

3. Systems Security

1. Cryptography
2. Operating Systems & Virtualisation Security
3. Distributed Systems Security
4. Formal Methods for Security
5. **Authentication, Authorisation & Accountability**

CyBOK - The Cyber Security Body of Knowledge

4. Software and Platform Security

1. **Software Security**
2. Web & Mobile Security
3. Secure Software Lifecycle

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5. Infrastructure Security

1. Applied Cryptography
2. **Network Security**
3. **Hardware Security**
4. Cyber Physical Systems
5. Physical Layer and Telecommunications Security

Network Security Example: Anomaly-Based Intrusion Detection

TABLE 21. Accuracy and false alarm rate scores for both data sets and models.

Data Set	Model	Accuracy	False Alarm Rate
Institutional	Ensemble Learning with SVM	0.9768	0.0010
	Ensemble Learning with KNN	0.9931	0.0010
	Ensemble Learning with Naive Bayes	0.9806	0.0011
	Ensemble Learning with Logistic Regression	0.9790	0.0010
	CNN	0.9968	0.0008
UNSW-NB15	Ensemble Learning with SVM	0.9902	0.0051
	Ensemble Learning with KNN	0.9960	0.0051
	Ensemble Learning with Naive Bayes	0.9818	0.0049
	Ensemble Learning with Logistic Regression	0.9896	0.0037
	CNN	0.9885	0.0041

E. Tufan *et al.*: Anomaly-Based Intrusion Detection by Machine Learning: A Case Study on Probing Attacks

Challenges in Anomaly Detection

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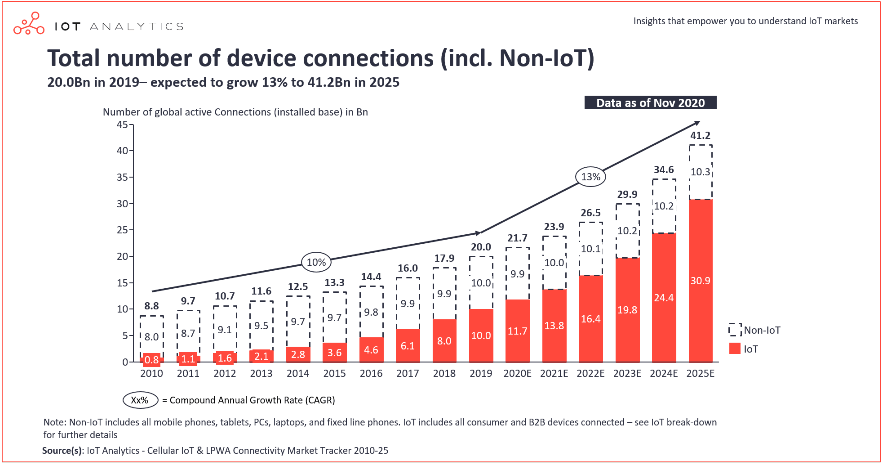
6. Use AI to simulate user behavior
7. AI Wars: Attackers also train their AI according to your AI

Who is Responsible for IoT Security



IoT connections, surpassing non-IoT for the first time:
`https://iot-analytics.com/state-of-the-iot-2020-12-billion-iot-connections-surpassing-non-iot-for-the-first-time`
Instead of securing every device, current approach is the collect all data, process it and then detect problems

Big Data and AI/ML

Big Data

"Big data is a field that treats ways to analyze, systematically extract information from, or otherwise deal with data sets that are too large or complex to be dealt with by traditional data-processing application software" - *Wikipedia*

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Artificial Intelligence and Machine Learning techniques can be used on big data

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Artificial Intelligence and Machine Learning techniques can be used on big data

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- to categorize data owners
- to score data owners

The Instagram Ads Facebook Won't Show You

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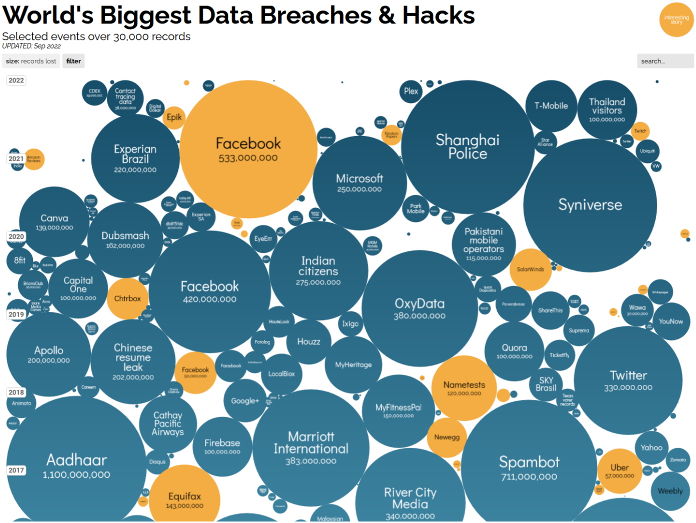
- But this transparency got them banned

Big Data Means Big Data Breaches



https://www.informationisbeautiful.net/visualizations/worlds-biggest-data-breaches-hacks

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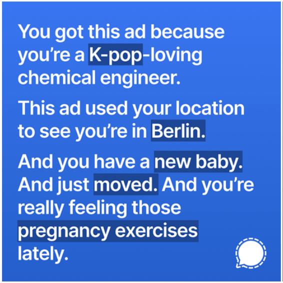

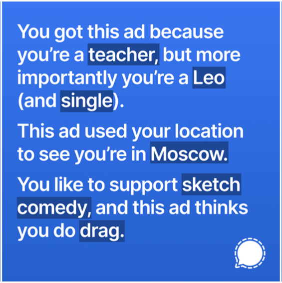

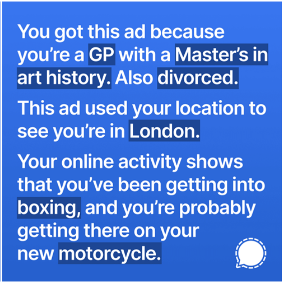

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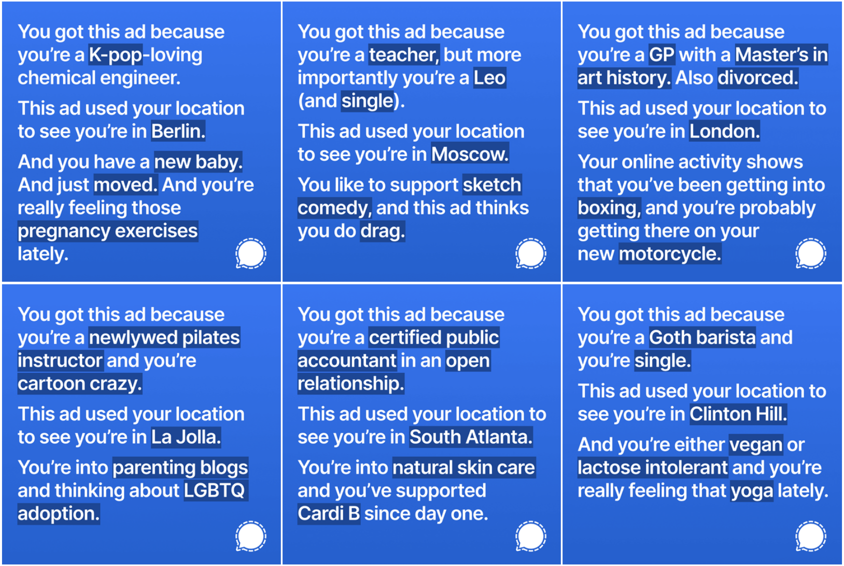

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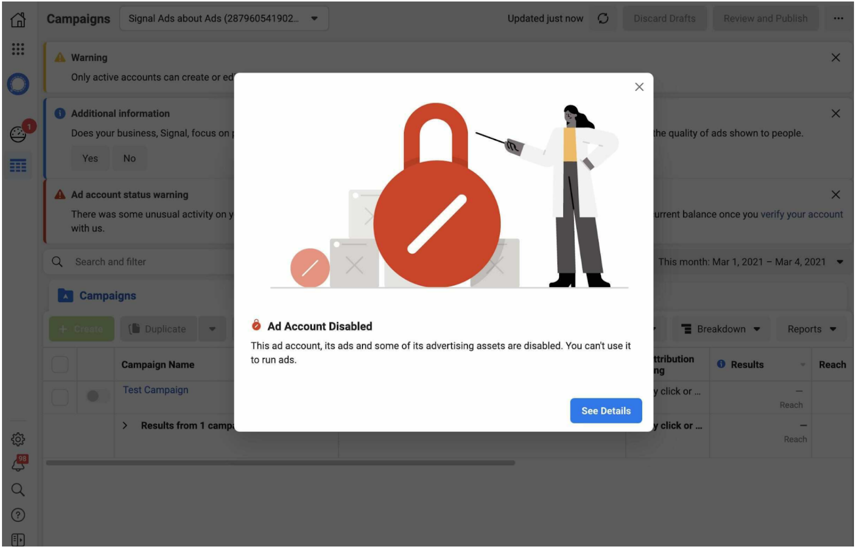

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- It was based on a GDPR-violation for processing the nationality of applicants by an ML algorithm in a discriminatory manner
- The algorithm had identified double citizenship systematically as high-risk, leading to marking claims by those individuals more likely as fraudulent

AI Fairness and Bias

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- Bias can be addressed prior to training the algorithm, during model training, and post-processing
- It is unclear how to avoid bias in practice

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- Because AI uses location info and the wealth is not equally distributed among the black and white people
- Thus, AI act racist because the data is biased

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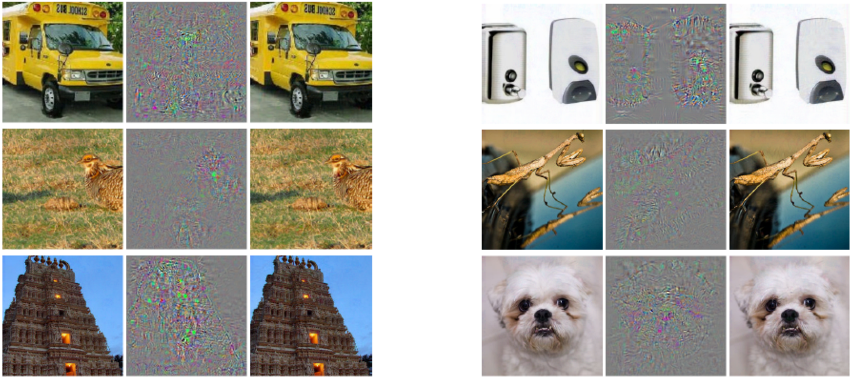
2. Use multi-party computation
3. Move your data from cloud to local solutions

Adversarial Models (Data Poisoning)



Szegedy *et al.* *Intriguing properties of neural networks*, 2nd International Conference on Learning Representations (ICLR) 2014

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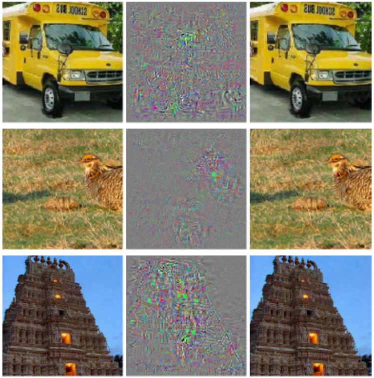

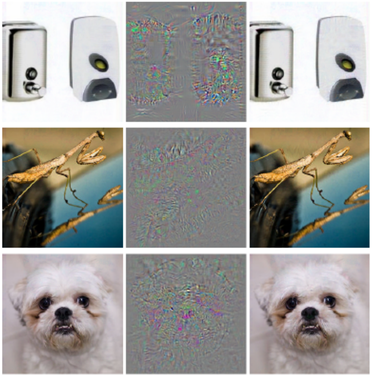

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Sağdaki resimleri yapay zeka modelleri Deve Kuşu zannediyor

Adversarial Models

https://www.wired.com/story/machine-learning-backdoors

Teşekkürler

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