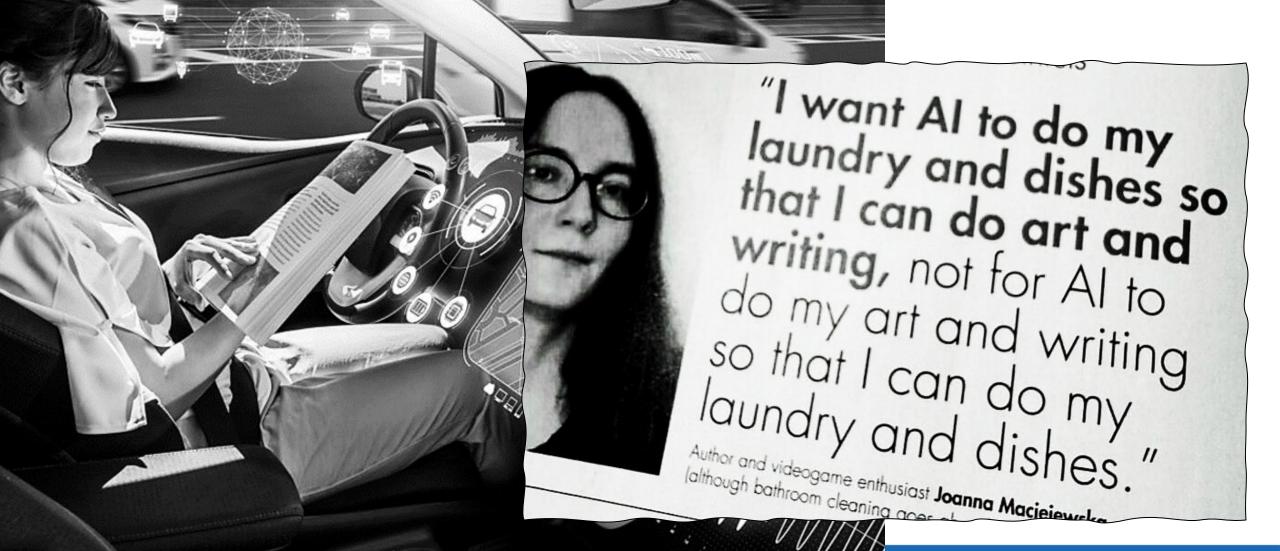


# Data Altruism

Machine Learning, honestly.





# **Models know**What you did last summer

#### A Survey of Privacy Attacks in Machine Learning

MARIA RIGAKI and SEBASTIAN GARCIA, Czech Technical University in Prague, Czech Republic

As machine learning becomes more widely used, the need to study its implications in security and privace becomes more urgent. Although the body of work in privacy has been steadily growing over the past few years, research on the privacy aspects of machine learning has received less focus than the security aspect Our contribution in this research is an analysis of more than 45 papers related to privacy attacks against machine learning that have been published during the past seven years. We propose an attack taxonom together with a threat model that allows the categorization of different attacks based on the adversarial knowledge, and the assets under attack. An initial exploration of the causes of privacy leaks is presented as well as a detailed analysis of the different attacks. Finally, we present an overview of the most commonly proposed defenses and a discussion of the open problems and future directions identified during our analysis.

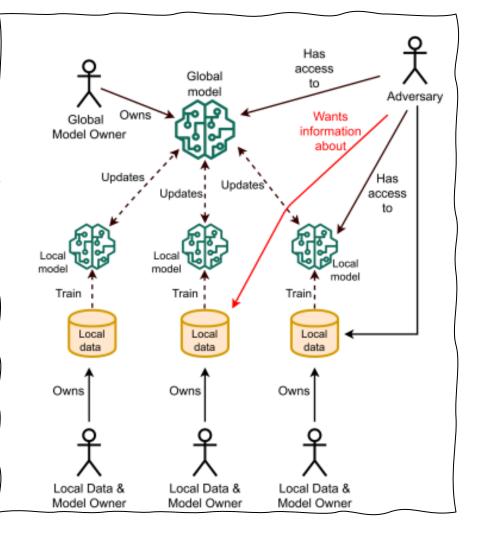
#### $CCS\ Concepts: \bullet\ Computing\ methodologies \rightarrow Machine\ learning; \bullet\ Security\ and\ privacy;$

Additional Key Words and Phrases: Privacy, machine learning, membership inference, property inference model extraction, reconstruction, model inversion

#### **ACM Reference format:**

Maria Rigaki and Sebastian Garcia. 2023. A Survey of Privacy Attacks in Machine Learning. ACM Compu Surv. 56, 4, Article 101 (November 2023), 34 pages.

https://doi.org/10.1145/3624010

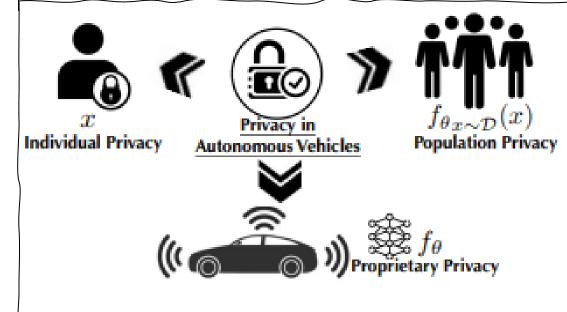


## Connected cars Eyes unseen, yet always near

#### Privacy of Autonomous Vehicles: Risks, Protection Methods, and Future Directions

Chulin Xie<sup>1</sup>, Zhong Cao<sup>2</sup>, Yunhui Long<sup>1</sup>, Diange Yang<sup>2</sup>, Ding Zhao<sup>3</sup>, Bo Li<sup>1</sup> <sup>1</sup>University of Illinois Urbana-Champaign <sup>2</sup>Tsinghua University <sup>3</sup>Carnegie Mellon University

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#### Fig. 1. Overview of privacy in autonomous vehicles.

#### TABLE II INDIVIDUAL PRIVACY: RISKS AND PRIVACY ATTACKS

Attack Category	Attack target	Adversary's Knowledge	Attack Method	Data Type	
Membership Inference	an is a	Black-box model, input distribution, model type	shadow model	location, imag tabular data [	
	Classification models	Black-box model	confidence-thresholding	location, imag text, tabular d	
merence		Black-box model	shadow dataset generation	image, tabula	
		Black-box model, average training loss	threshold-based	tabular data [	
		Black-box model, input distribution, model type	shadow model, robustness evaluation	images, locati	
· ·	Generative models	White/Black-box model	confidence-thresholding, GAN	images [79]	
		Black-box model	latent encoding	images [80]	
·	Aggregated statistics	Black-box model, prior observation	game-based procedure	location [81]	
Model	Classification	White/Black-box model	optimization-based	image, tabular	
Inversion	models	Black-box model, public data	inversion model	image [82]	
		White-box model, public data, corrupted target input	GAN	image [83]	
Model Memorization	Classification models	White/Black-box model	encoding	image, text [8	
	Generative models	White-box model	random sequences insertion	text [13]	

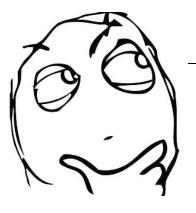
INTERNATIONAL STANDARD

**ISO/IEC** 5338

First edition 2023-12

# Information technology — Artificial intelligence — AI system life cycle processes

Technologies de l'information — Intelligence artificielle — Processus de cycle de vie des systèmes d'IA



### Data is the heartbeat of everything

Artificial Intelligence Life Cycle

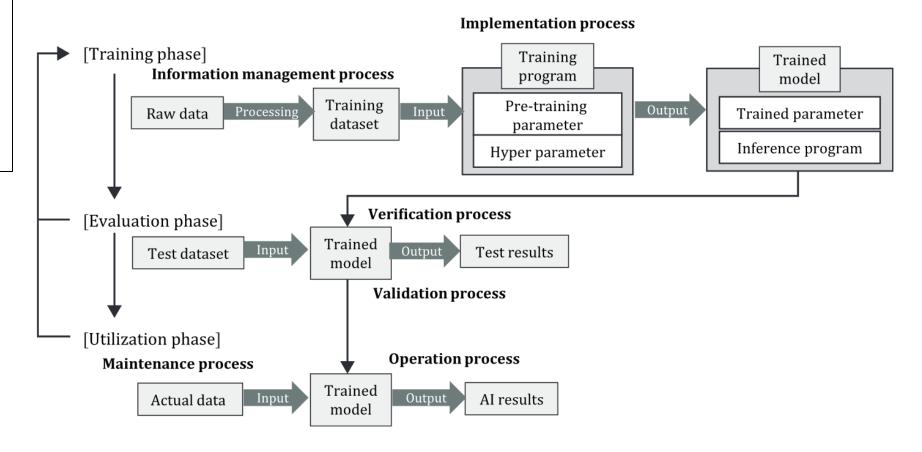


Figure A.1 — The flow of AI-specific processes

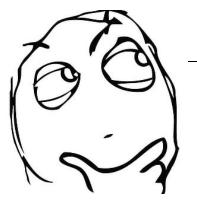
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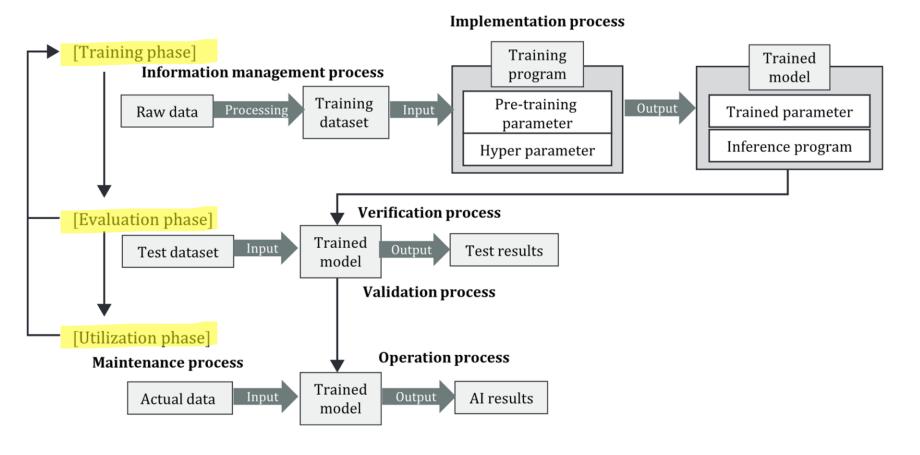
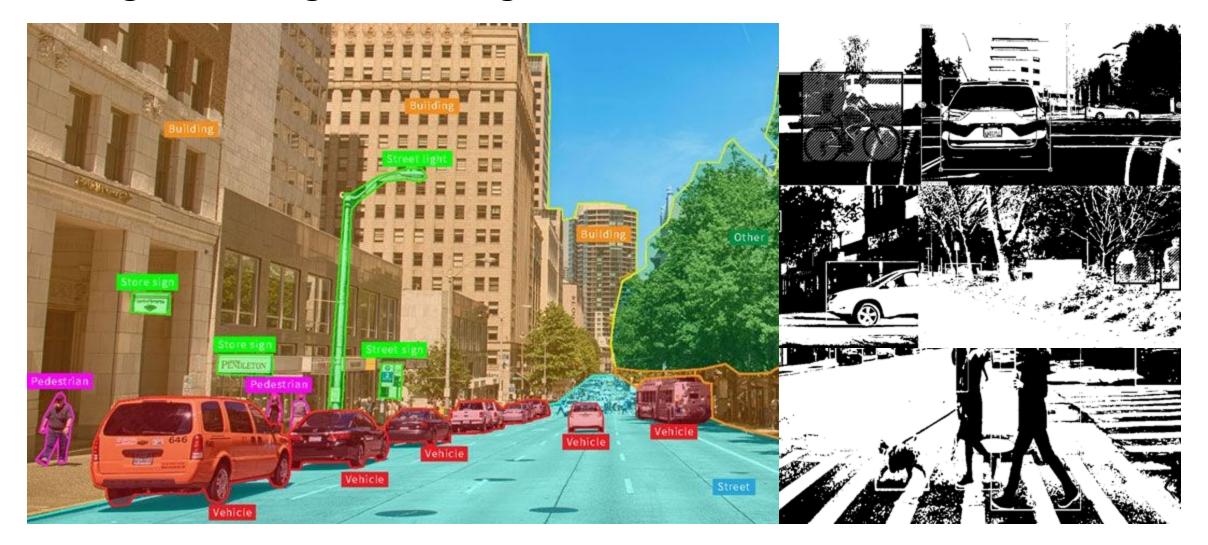


Figure A.1 — The flow of AI-specific processes



#### From life's chaos, data brings order

Through bounding boxes & segmentation





#### Data moves at the speed of light

The law struggles to catch it





#### Neural networks feast on data

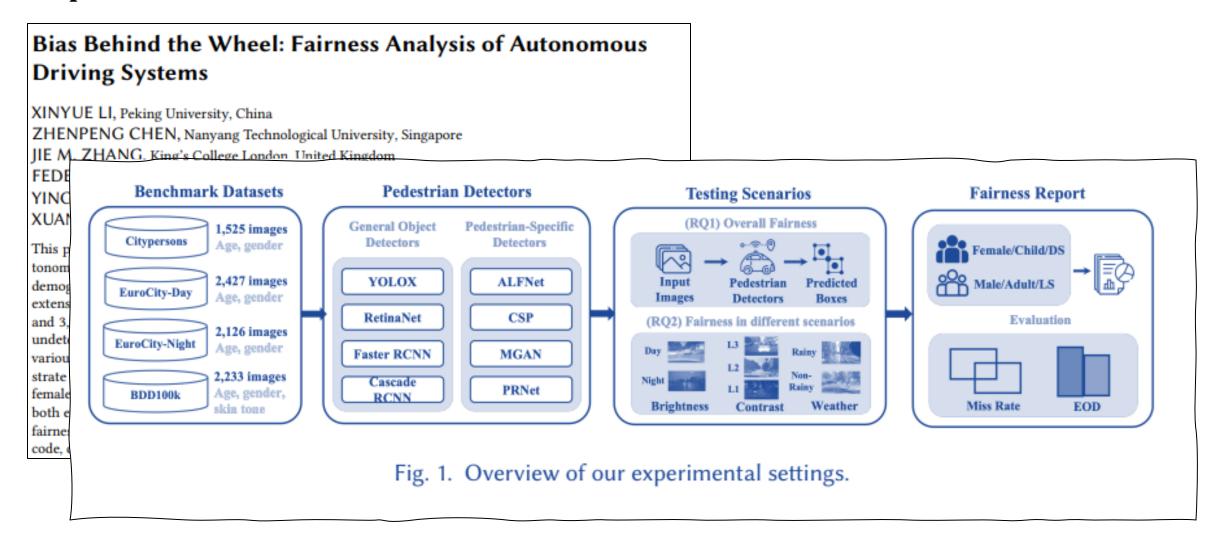
#### To reinforce stability and safety



Feng, S., Sun, H., Yan, X. et al. Dense reinforcement learning for safety validation of autonomous vehicles. *Nature* **615**, 620–627 (2023).

#### Autonomous driving's fairness

#### Depends on inclusive data



# **Diverse data saves lives**Without it, systems fail

Table 4. Number of labeled pedestrian instances per dataset.

	Gender		Ag	ge	Skin tone		
Dataset	Male	Female	Adult	Child	Light	Dark	
CityPersons	2,357	1,822	4,568	233	-	-	
EuroCity-Day	1,726	1,646	4,498	100	-	-	
EuroCity-Night	1,265	1,318	4,165	68	-	-	
BDD100k	3,457	2,479	6,293	190	2,724	789	
Overall	8,805	7,265	19,524	591	2,724	789	

		Day-time	:	Night-time				
Detectors	MR Adult	MR Child	EOD (Age)	MR Adult	MR Child	EOD (Age)		
YOLOX	10.80%	40.77%	-29.97%	17.81%	54.93%	-37.12%		
RetinaNet	12.73%	41.92%	-29.19%	18.97%	61.97%	-43.01%		
Faster RCNN	4.50%	25.00%	-20.50%	7.34%	33.80%	-26.46%		
Cascade RCNN	4.52%	25.58%	-21.05%	6.81%	33.80%	-26.99%		
ALFNet	26.52%	49.42%	-22.90%	65.10%	83.10%	-18.00%		
CSP	28.64%	46.92%	-18.28%	63.42%	76.06%	-12.64%		
MGAN	27.87%	43.46%	-15.59%	49.72%	69.01%	-19.30%		
PRNet	34.80%	56.92%	-22.13%	72.60%	92.96%	-20.36%		
Average	18.80%	41.25%	-22.45%	37.72%	63.20%	-25.48%		

Age

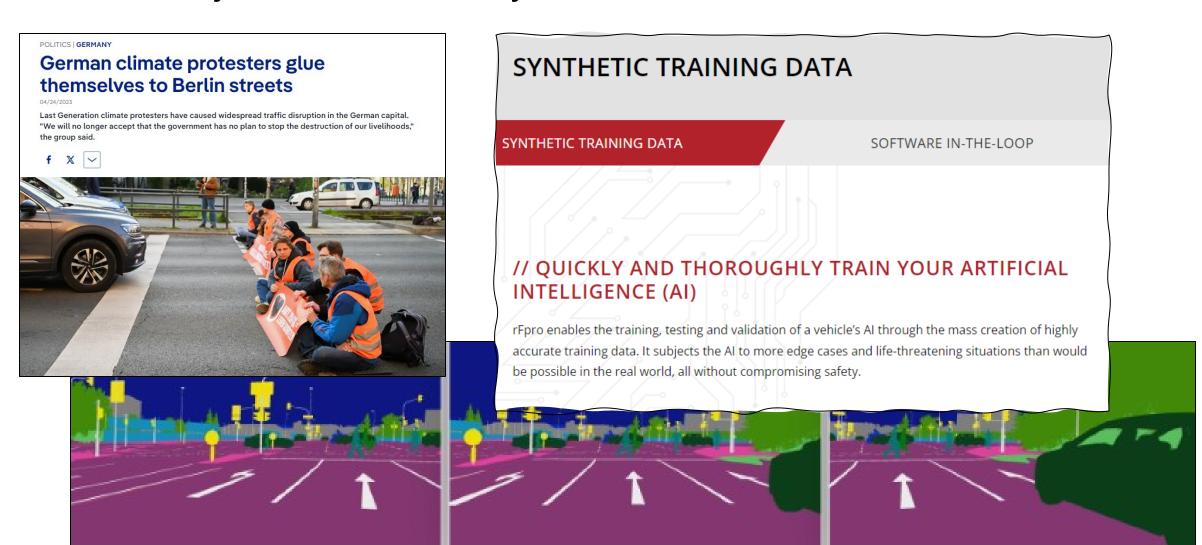
## Diverse data saves lives

#### Without it, systems fail

Table 4. Num	ber of la	abeled p	edestrian instance	es per dataset.					EOD	(Age)	
	Ge	ender	Age	Skin tone	_				-29	.97%	
Dataset	Male	Femal	· Ασ	e					-29	.19%	
CityPersons EuroCity-Day EuroCity-Night	2,357 1,726 1,265	1,822 1,646 1,318		Child					-20	.50%	
BDD100k Overall	3,457	2,479		Ciniu				Age	-21	.05%	
Overall	8,805	7,26	4,568	233	-	I	Day-time		-22	.90%	
			4,498	100	Detectors	MR Adult	MR Child	EOD (Age)	-18	.28%	DD (Age)
			4,165	68	YOLOX RetinaNet aster RCNN	10.80% 12.73% 4.50%	40.77% 41.92% 25.00%	-29.97% -29.19% -20.50%		.59%	-37.12% -43.01% -26.46%
			6,293	190	scade RCNN ALFNet	4.52% 26.52%	25.58% 49.42%	-21.05% -22.90%	-22	.13%	-26.99% -18.00%
			19,524	591	CSP MGAN PRNet	28.64% 27.87% 34.80%	46.92% 43.46% 56.92%	-18.28% -15.59% -22.13%	-22	.45%	-12.64% -19.30% -20.36%
		(			Average	18.80%	41.25%	-22.45%	37.72%	63.20%	-25.48%

#### The model's manifold grows

#### With each layer of data diversity



#### Comprehensive, diverse data

#### The lifeblood of accurate medical AI

Article Published: 18 May 2020

# A deep learning system for differential diagnosis of skin diseases

Yuan Liu, Ayush Jain, Clara Eng, David H. Way, Kang Lee, Peggy Bui, Kimberly Kanada, Oliveira Marinho, Jessica Gallegos, Sara Gabriele, Vishakha Gupta, Nalini Singh, Vivek Hofmann-Wellenhof, Greg S. Corrado, Lily H. Peng, Dale R. Webster, Dennis Ai, Susan

End-to-end lung cancer screening with three-

Letter | Published: 20 May 2019

dimensional deep learning on low-dose chest computed tomography

<u>Diego Ardila, Atilla P. Kiraly, Sujeeth Bharadwaj, Bokyung Choi, Joshua J. Reicher, Lily Peng, Daniel Tse</u>

Nature Medicine 26, 900-908

R. Carter Dunn & David Coz

23k Accesses 377 Citations

Original Investigation | Innovations in Health Care Delivery

December 13, 2016

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Varun Gulshan, PhD<sup>1</sup>; Lily Peng, MD, PhD<sup>1</sup>; Marc Coram, PhD<sup>1</sup>; et al

» Author Affiliations | Article Information

JAMA. 2016;316(22):2402-2410. doi:10.1001/jama.2016.17216

lo, David P. Naidich & Shravya Shetty

this article

tmetric | Metrics

# **Protectionism**Will not last forever



Der Hamburgische Beauftragte für Datenschutz und Informationsfreiheit

Diskussionspapier: Large Language Models und personenbezogene Daten

- Die bloße Speicherung eines LLMs stellt keine Verarbeitung im Sinne des Art. 4 Nr. 2
  DSGVO dar. Denn in LLMs werden keine personenbezogenen Daten gespeichert. Soweit in
  einem LLM-gestützten KI-System personenbezogene Daten verarbeitet werden, müssen
  die Verarbeitungsvorgänge den Anforderungen der DSGVO entsprechen. Dies gilt insbesondere für den Output eines solchen KI-Systems.
- 2. Mangels Speicherung personenbezogener Daten im LLM können die Betroffenenrechte der DSGVO nicht das Modell selbst zum Gegenstand haben. Ansprüche auf Auskunft, Löschung oder Berichtigung können sich jedoch zumindest auf Input und Output eines Kl-Systems der verantwortlichen Anbieter:in oder Betreiber:in beziehen.
- 3. Das Training von LLMs mit personenbezogenen Daten muss datenschutzkonform erfolgen. Dabei sind auch die Betroffenenrechte zu beachten. Ein ggf. datenschutzwidriges Training wirkt sich aber nicht auf die Rechtmäßigkeit des Einsatzes eines solchen Modells in einem KI-System aus.

#### Data Altruism By Design

Carving out a GDPR exception for Machine Learning

1.Lawful access

2. The storing of the data is not the purpose

3. The systems aren't used to the detriment of the data subjects or in a way that

4. Reversed burden of proof

5. Point 4 includes implementing appropriate TOMs throughout the AI lifecycle

An insurance fund to cover risks.

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