







Foundations of Robustness and Reliability in AI

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# Can artificial intelligence be relied upon?



### **PIGS ON WINGS**



Al sees "pig"

+ 0.005 x



Invisible noise



Al sees "airplane"



	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%





### FOUNDRY's mission statement

«Develop the theoretical foundations of robustness and reliability in machine learning and artificial intelligence»

### The challenges ahead

- 1. The « known unknowns »
- 2. The « unknown unknowns »
- 3. Balance concurrent desiderata

*#adversarial attacks #data-centric impediments* 

#multi-agent learning #online adaptation

*#fairness #privacy # strategic agents* 



### **Research Axes**

#### 1. Tame the «known unknowns»

- Robustness to data-centric impediments («bad data»)
- Shortfalls in the data (incomplete observations, label shifts, poisoning)
- Impediments at inference time (adversarial attacks,...)

## 2. Adapt to the «unknown unknowns»

- Adaptivity to unmodeled phenomena and/or the environment
- From best- to worst-case guarantees
- Adapt « on the fly » to nonstationary environments

- 3. Balance concurrent / incompatible objectives
  - Robustness v. accuracy
  - Guarantees in privacy and/or fairness vs. predictive accuracy
  - Selfishly-minded agents



# The partners







### Skills and expertise

### **Machine Learning**



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## Consortium breakdown

• POLARIS (lead: P. Mertikopoulos)

# game theory #optimization #online learning #reinforcement learning

• ENSL (A. Garivier)

#sequential statistics #bandits #reinforcement learning #differential privacy

• FAIRPLAY (P. Loiseau)

#matching #fairness #privacy #online learning #online algorithms

LTCI (F. D'Alché-Buc)

#extreme value theory #robust statistics #structure data #Monte Carlo

• MILES (Y. Chevaleyre)

#adversarial models #game theory #deep learning #computational learning

• SCOOL (E. Kaufmann)

#reinforcement learning #bandits #non-parametric methods #privacy



# Targeted outcomes & collaborations



### Work breakdown structure

### 1. WP1: Resilience to data-centric impediments

- Robustness against corruptions and contaminations
- Risk-aware learning with robustness guarantees
- Adversarial robustness and reliability

### 2. WP2: Adaptivity to unmodeled phenomena and the environment

- Robust multi-agent learning
- Learning in coopetitive environments
- Learning unmodeled structures

### 3. WP3: Robustness in the presence of concurrent aims and goals

- Fairness-driven trade-offs
- Privacy-driven trade-offs
- Robust multi-objective machine learning



#### WP1: RESILIENCE TO DATA-CENTRIC IMPEDIMENTS

	Т0-Т6	T6–T12	T12–T18	T18–T24	T24–T30	T30–T36	T36–T42	T42–T48
Task 1.1			LTCI PhD: Data depth for robustness to contaminations					
Corruptions & Contaminations			SCOOL PhD: Co	rruption and miss	l pecified structures I	s in bandits	 	
Task 1.2	SCOOL PhD: Ris	k-aware model-ba	l ased reinforcemen I	t learning				
Risk-aware Learning with Robustness Guarantees		ENSL PD: Risk-aware planning in MDPs EN				ENSL PD: Risk-awareness in RL		
			POLARIS PhD:	Robust reinforcem	ent learning in ME	)Ps		
<b>Task 1.3</b> Adversarial Robustness and Reliability	LTCI PhD: Robus	t and reliable stru	l ctured output pred	diction				
	MILES PD: Adve	rsarial robustness	in large ML model	S			D1.2: stat-anor	n / robust-struct
			LTCI PD: Confide	ence and robustne	ss certificates		D1.4	provably-robust
			MILES PhD: Prov	vable robustness v	ia optimal transpo	rt		
	!		·		D1.1: rl-berry	D1.3	DRL simulator	



#### WP2: ADAPTIVITY TO UNMODELED PHENOMENA AND THE ENVIRONMENT

	то-т6	T6–T12	T12–T18	T18–T24	T24–T30	T30–T36	T36–T42	T42–T48	
<b>Task 2.1</b> Robust Multi-agent Learning	POLARIS PhD: Robustness to stochastic perturbations in game-theoretic learning								
			POLARIS PhD:	Robust learning wi	th self-motivated a	agents			
			MILES PhD: Bou	inded rationality ir	stochastic games				
Task 2.2		FAIRPLAY PhD:	Coopetitive multi	-agent learning					
Learning in Coopetitive Environments		FAIRPLAY PhD:	l Fairness in coopet	titive multi-agent s	l ystems				
			POLARIS PD: U	niversal algorithms	। s for multi-agent le ।	arning			
Task 2.3		FAIRPLAY PD: L	PLAY PD: Learning random structures				<b>D2.2:</b> GameSe	er	
Learning Unmodeled Structures		FAIRPLAY PD: N	l Aatching with learn	ned preferences					
	SCOOL PD: Rob	ust non-parametri	c algorithms for st	ructured bandits					
	1	1	D	2.1: monograph	1	1	I	<b>D2.3:</b> book	



#### WP3: ROBUSTNESS IN THE PRESENCE OF CONCURRENT AIMS AND GOALS

	Т0-Т6	T6–T12	T12–T18	T18–T24	T24–T30	Т30–Т36	T36–T42	T42–T48	
Task 3.1	MILES PhD: Fairness in generative models						<b>D3.3a:</b> gen-fair		
Fairness-driven Trade-offs in Machine Learning	LTCI PhD: Fairness-utility trade-offs Rank-based techniques for fair statistical learning						D3.3b: fair-net		
			LTCI PhD: Rank-	based techniques	for fair statistical l	earning			
Task 3.2	ENSL PhD: Statistical trade-offs of differential privacy								
Privacy-driven Trade-offs in Machine Learning			SCOOL PhD: Co	st of privacy in ada	aptive testing				
			FAIRPLAY PD: P	rivacy & incentive	s for data release	D3.2: marketpl	ace simulator		
T. J. 7 7			FAIRPLAY PhD:	Fairness with priva	acy in online learn	ing			
Robust Multi-Objective Machine Learning		POLARIS PhD: Robust mechanism design for high-stakes applications							
			LTCI PD: Robust	multi-objective lea	anring on graphs				
			SCOOL PD: Rob	ustness to non-cor	npliant agents in I	RL			
			1		D3.1: rl-berry				

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## Outreach, output & dissemination

### Hirings

- # 4 PhDs, 1 post-doc (FAIRPLAY, SCOOL
- # CNRS, ENSL, Dauphine held back by contracting

### Industrial outreach

- # Criteo (FAIRPLAY, POLARIS)
- # Ubisoft (ENSL)

### **Output & dissemination**

- # Leading ML conferences (NeurIPS, ICML,...)
- # See posters in the lobby









