







# Spoke 1 Human-Centered AI

Dino Pedreschi Università di Pisa



# Future Artificial Intelligence Research



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Ministero dell'Università e della Ricerca







**Consiglio Nazionale** delle **Ricerche** 



**SCUOLA NORMALE SUPERIORE** 









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SNS (5) Benzi Michele Giannotti Fosca Pellungrini Roberto Squartini Tiziano Trenz Hans-Joerg CNR (9) Boldrini Chiara Conti Marco Fabrizio Falchi Nanni Mirco Passarella Andrea Perego Raffaele Rinzivillo Salvatore Sebastiani Fabrizio Straccia Umberto

Spoke 1 - Critical Mass 39 persons 9 UniPI Departments 2 CNR Institutes 2 SNS Classes









# **Spoke 1: the research questions**

### 1) "human-in-the-loop" machine learning and reasoning:

how humans and AI interact synergistically in complex (decision making) tasks (WP1.1-2-3)

### 2) social-aware AI:

how to understand and govern the societal outcomes of large-scale socio-technical systems of humans and Als (WP1.4-5)

### 3) design of trustworthy AI systems:

how to the responsibly (co-)design, develop, validate and use trustworthy AI systems (WP1.6)

Extensive **experiments, case studies and pilots** of H-AI systems (WP1.7)

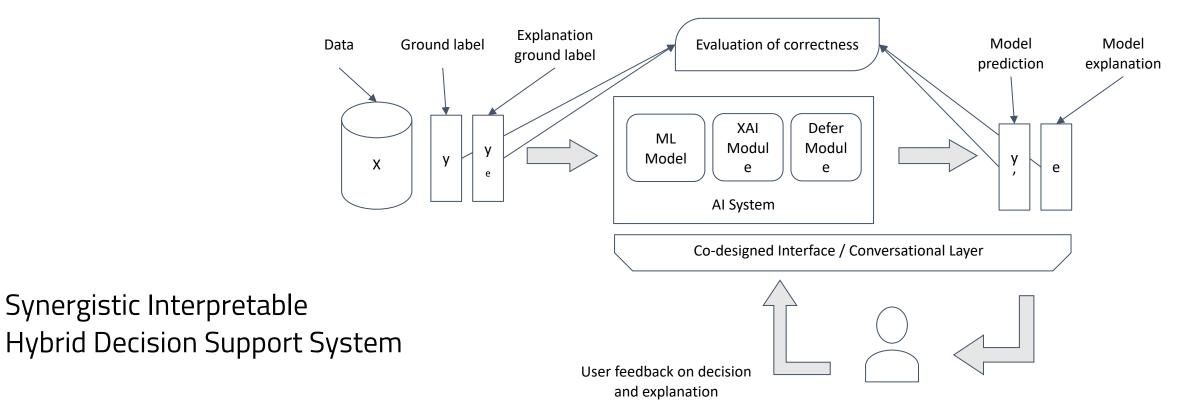








# WP1.1 - Explainable AI for synergistic Human-AI collaboration Task lead: SNS, co-PIs: Fosca Giannotti, Riccardo Guidotti.







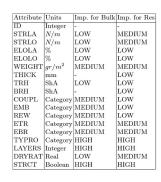


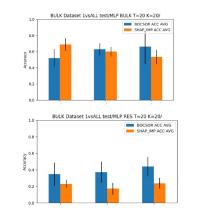


# WP1.1 - Explainable AI for synergistic Human-AI collaboration Task lead: SNS, co-PIs: Fosca Giannotti, Riccardo Guidotti.

Industrial Case Study

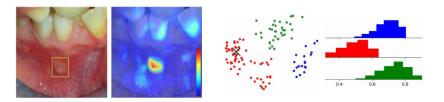
- Machines to manufacture tissue paper.
- Production features can be used to predict paper bulk and resistance.
- Experts provided importance of these features as high, medium, low.

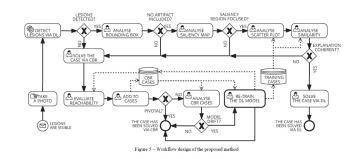




Medical Case Study

- Case-Based Reasoning + ML models + XAI for decision support system
- Final decision taken by resident doctors or specialized ones depending on XAI impact.













WP1.2 – "System1 and System2" Machine Learning and Reasoning Task lead: CNR, co-PIs: Umberto Straccia, Salvatore Ruggieri

#### **Ontology-based learning and reasoning**

#### Mammography patient data

Patient	hasDensity	hasShape	hasMargin	hasBiRads	hasAge	
p0	low	lobular	spiculated	5	67	
p10	high	irregular	spiculated	5	76	
p102	-	irregular	ill-defined	4	58	
p108	low	round	circumscribed	4	57	
p109	-	irregular	ill-defined	5	33	
p110	low	irregular	ill-defined	4	45	
p111	low	irregular	ill-defined	5	71	

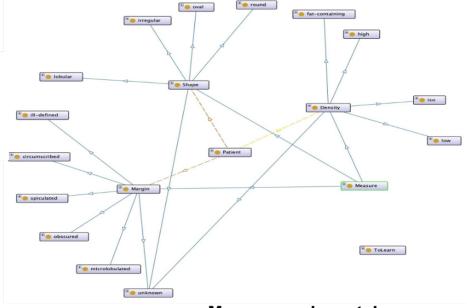
#### Learn Rules to Classify:

• Does a patient have breast cancer?

#### Example of learnt rule:

(hasMargin III-defined) AND (hasShape Irregular) AND (hasAge Old) ==> Cancer, 0.853

*IF* there is an image region whose margin is *ill-defined* **AND** whose shape is irregular **AND** the person is old *THEN* the mammography is about a tumor



Mammography ontology







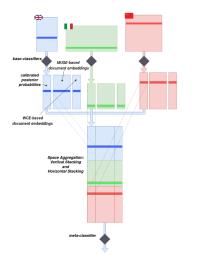


# WP1.3 - Human centered Lifelong Learning for Complex Data

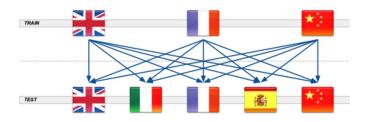
Task Lead: UNIPI, co-PIs: Alessio Micheli, Fabrizio Sebastiani

# Cross-Lingual Text Classification (CLTC):

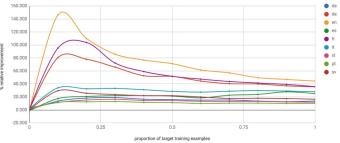
• Goal: leverage training data in a source language (e.g., EN) for classifying data in a target language (e.g., IT) when training data in the target language are scarce (zero-shot CLTC) or few (few-shot CLTC)



- Developed Generalized Funnelling, a "heterogeneous transfer learning" architecture that allows this
- In the zero-shot case, allows training a classifier for the target language
- In the few-shot case, radical improvements in classification accuracy
- Will be tested in "continual learning" scenarios











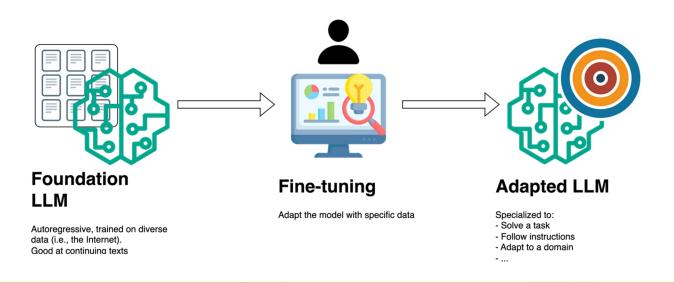




# WP1.3 - Human centered Lifelong Learning for Complex Data

Task Lead: UNIPI, co-PIs: Alessio Micheli, Fabrizio Sebastiani

- Large Language Models (LLMs) exhibit impressive abilities on several tasks (despite not being directly trained on them)
- LLMs still face issues on domain-specific applications (e.g., legal, medical, financial etc.), which can be overcome with domain adaptation via further-pretraining and fine-tuning











# WP1.4 - Human-Al Socio-technical Complex Systems Task lead: UNIPI, co-PIs: Dino Pedreschi, Chiara Boldrini

### Social networks & Al

- Echo chamber detection, detection of influential nodes, spot the presence of emerging collective phenomena, simulation of human and AI agents
- FOCUS: understand how AI-mediated information flows in a STS

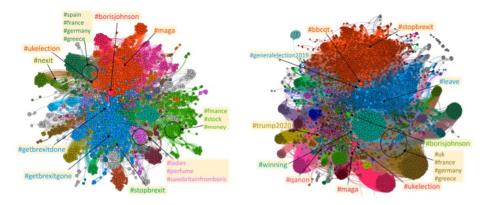


Figure 8: The backbone of the network of hashtags and bots (left) or suspended users (right) linked by retweets for the whole period of our dataset. Both networks show a modular structure probably due to the coordination of the automated users: the depicted partitions have a modularity of 0.73 (left) and 0.78 (right). In the bots' network the Brexit discussion appears together in the blue community, while for the suspended users two separate groups are pro-Euro (orange) and pro-Brexit (blue). In both cases, Trump-related hashtags are very common.









# WP1.4 - Human-Al Socio-technical Complex Systems Task lead: UNIPI, co-PIs: Dino Pedreschi, Chiara Boldrini

# Self-organization & individual vs collective goals in STS

 Impact of GPS navigation apps on urban emissions: egoistic vs collective approach



 Decentralized learning in a network of smartphones with no central server

	Method	Avg accuracy
Standalone baselines	Centralised	0.9824
Standarone baselines	ISOL	0.6473
Distributed baseline	FED	0.9410
	DecHetero	0.9071
Decentralised SOTA	CFA	0.8975
	CEA CE	0.9460
Decentralised Proposal	DecDiff+VT	0.9530

### better than Federated!





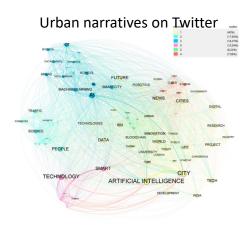


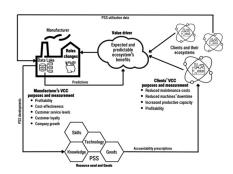


# WP1.4 - Human-Al Socio-technical Complex Systems Task lead: UNIPI, co-PIs: Dino Pedreschi, Chiara Boldrini

### Social and economic impact of AI-STS

- AI & sustainable cities
  - citizens' opinions on urban experiences and visions using big data and AI applications
- AI & affordable and clean energy
- Al for business and economics
  - interpretive framework to understand how machine learning (ML) affects the way companies interact with their ecosystem and how the introduction of digital technologies affects the value co-creation (VCC) process
  - how AI algorithms can be used to predict resolution of bankruptcy procedures













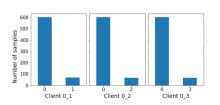
### WP1.5 – Decentralized, Cooperative Learning

Task lead: CNR, co-PIs: Raffaele Perego, Francesco Marcelloni

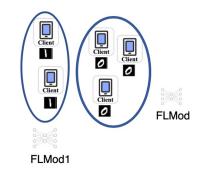
#### Learning on resource-constrained devices (small memory, battery-operated)

- Energy-aware learning of neural networks at the edge
  - We contributed a solution for memory-aware pruning of neural networks at learning time
  - Working on a novel "energy-aware" technique for NN pruning
    - Modeling the energy footprint of different neural network architectures
    - Pruning as the problem of finding the network that maximizes the accuracy with the smallest amount of energy used
    - Experiments on NVIDIA Jetson on a image classification task
- Anomaly Detection with Decentralised Unsupervised Federated Learning
  - System properties
    - Local anomalies might not be global anomalies: the "normal" behaviour for a node could be anomalous of another one;
    - Data Locality: Nodes can access only a limited portion of data;
    - Nodes have limited resources and train tiny ML models (e.g., Autoencoders) with limited capacity for identifying the anomalous patterns.
  - **Goal**: to go beyond the local representations by extending the generalisation capability of local models.
  - **How**: by identifying which other nodes share the same categories to initiate a federated collaboration for improving the local model

#### Data distribution across nodes



- 1. Find communities of peers
- 2. Perform per-community Federated Learning





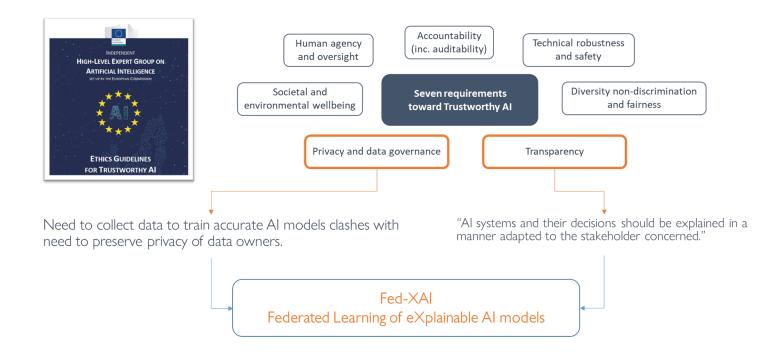






## WP1.5 – Decentralized, Cooperative Learning

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#### WP1.5 – Decentralized, Cooperative Learning

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#### Deployment of components

- Containers as de-facto standard for Lightweight Virtualization
- Compliance with edge-computing / MEC-enabled environments



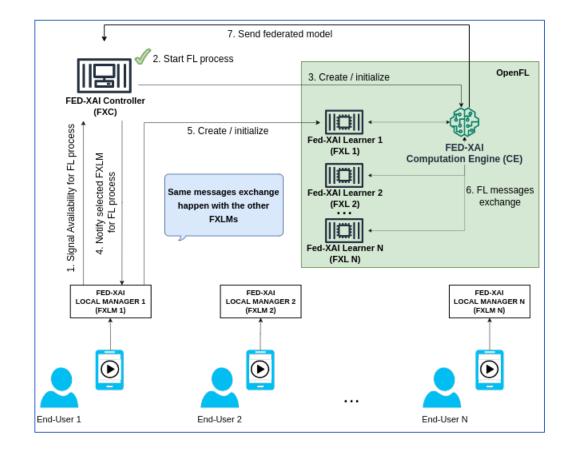
#### <u>Message exchange</u>

- **RestAPIs** for handling and integrating app microservices
- Over HTTPS: encryption for secure communication

#### intel/**openfl**

#### Federated Learning Framework

- Intel OpenFL
- Seamless integration with containers paradigm
- Extended to support FL of inherently interpretable models











# WP1.6 - Co-design methodologies for trustworthiness-by-design

Task lead: UNIPI, co-PIs: Adriano Fabris, Anna Monreale

- Development of specific codes of conduct, depending on the needs of companies, regarding the use in their areas of AI programs or devices
- Ethics and legal counseling with respect to compliance with European regulations (Al Act)
- Advice regarding risk assessment related to privacy compliance
- Multidisciplinary Laboratory for the Study and Certification of Safe, Trustworthy, and Ethical AI Systems





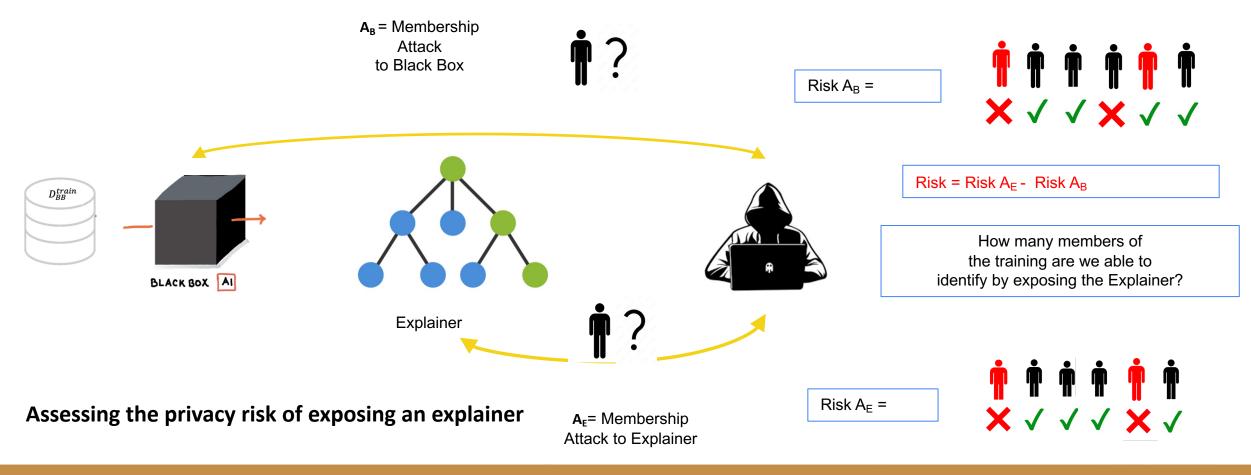






### **WP1.6** - Co-design methodologies for trustworthiness-by-design

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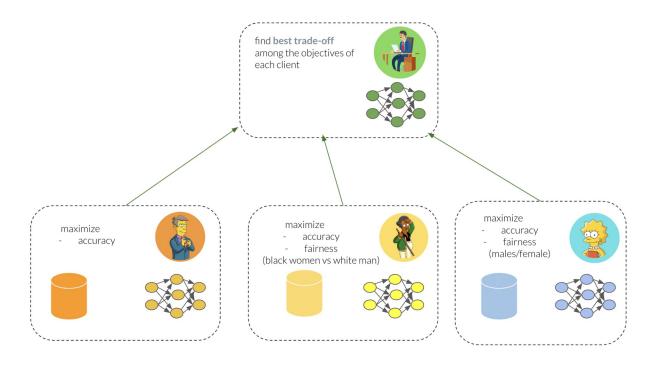




# WP1.6 - Co-design methodologies for trustworthiness-by-design

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# **GLOFAIR** (Global-Local Optimization for Fairness in Federated Learning)



#### Designing collaborative learning where:

- each predictive local model is the result of a multiobjective learning process
- each local client has its own set of objectives
   (fairness, utility, ...)
- Train the models without modifying or moving the private training data



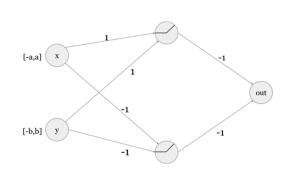






# WP1.6 - Co-design methodologies for trustworthiness-by-design Task lead: UNIPI, co-PIs: Adriano Fabris, Anna Monreale

Predictability and reliability of multi-layer perceptron models for non-linear regression applications Example: bounds on the output of a cruise controller for Advanced Driver Assistance Systems (ADAS)



x ∈ [-a, a] y ∈ [-b, b]

relu(x) = x if x > 0, 0 otherwise



BEGIN
<pre>xinreal: TYPE = { r: real   r&gt;=-a AND r&lt;=a} yinreal: TYPE = { r: real   r&gt;=-b AND r&lt;=b}</pre>
relu (x: real): real = IF x > 0 THEN x ELSE 0 ENDIF
<pre>input_neuron (x: xinreal, y: yinreal): real = relu(x+y) hidden_neuron (x: real, y: real): real = relu(x+y) output_neuron (x: real, y: real): real = -(x+y);</pre>

qfcnn [a: { x: real | x>0 }. b: { x: real | x>0 }]: THEORY

network (x: xinreal, y: yinreal): real = output\_neuron(input\_neuron(x,y),input\_neuron(-x,-y))

network\_bounds: THEOREM
FORALL (x:xinreal, y: yinreal): network(x,y) >= -(a+b)

END gfcnn









### WP1.7 – Empirical studies and pilots of human centered AI

Task lead: UNIPI, co-PIs: Francesco Marcelloni, Raffaele Perego, Salvatore Ruggieri, Dino Pedreschi

#### Industrial applications

- Increase workplace safety through sensors and artificial intelligence (in collaboration with INAIL)
- Extracting and identifying engineering relations between Engineering Design entities from technical documents
- Extraction of **flowcharts** from patent descriptions and images
- Reducing the gap between the academic world and the job market by improving the matching between job advertisements and offerings
- Evaluation of an expressive social robot cognitive system by means of **natural human-robot interaction and dialogue**













# WP1.7 – Empirical studies and pilots of human centered AI

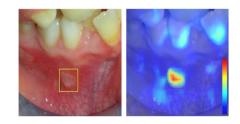
Task lead: UNIPI, co-PIs: Francesco Marcelloni, Raffaele Perego, Salvatore Ruggieri, Dino Pedreschi

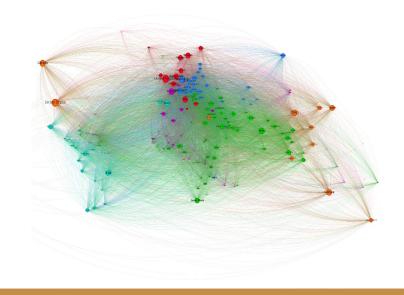
### **Medical Applications**

- Oral squamous cell carcinoma detection and classification
- Analysis of the effects of different diets on 24-hour core body temperature and energy metabolism

### Society

- Analysis of the impact of AI systems in territorial and urban contexts, along with other socio-economic and environmental factors
- Exploring urban mobility through GeoAl













# WP1.7 – Empirical studies and pilots of human centered AI

Task lead: UNIPI, co-PIs: Francesco Marcelloni, Raffaele Perego, Salvatore Ruggieri, Dino Pedreschi

### Archaeology

- **Urban Archaeology**: AI-controlled robotic arm for classification and selection of archaeological ceramic fragments
- Environmental Archaeology: AI approaches for animal bones recognition and landscape reconstruction
- **Sub-AI**: Project to interpret, digitally share, and document underwater archaeological heritage, as well as determine its ecological effects on local biological communities
- Contemporary Archaeology: Digital traces of migration in Lampedusa

