Assessing the impact of AI on human behaviour: interdisciplinary views

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Joint work/slides from Vicky Charisi, Marius Miron, Songül Tolan, Nando Martínez-Plumed, Enrique Fernández-Macías, Annarosa Pesole, Maria Iglesias (JRC); Carlos Castillo, Lorenzo Porcaro (UPF); José H. Orallo (UPV); Luis Merino, Fernando Caballero (UPO); Bob Sturm (KTH); Emilio Gómez-González (US)

Outline

- Motivation
- Interdisciplinarity and diversity
- Selected projects

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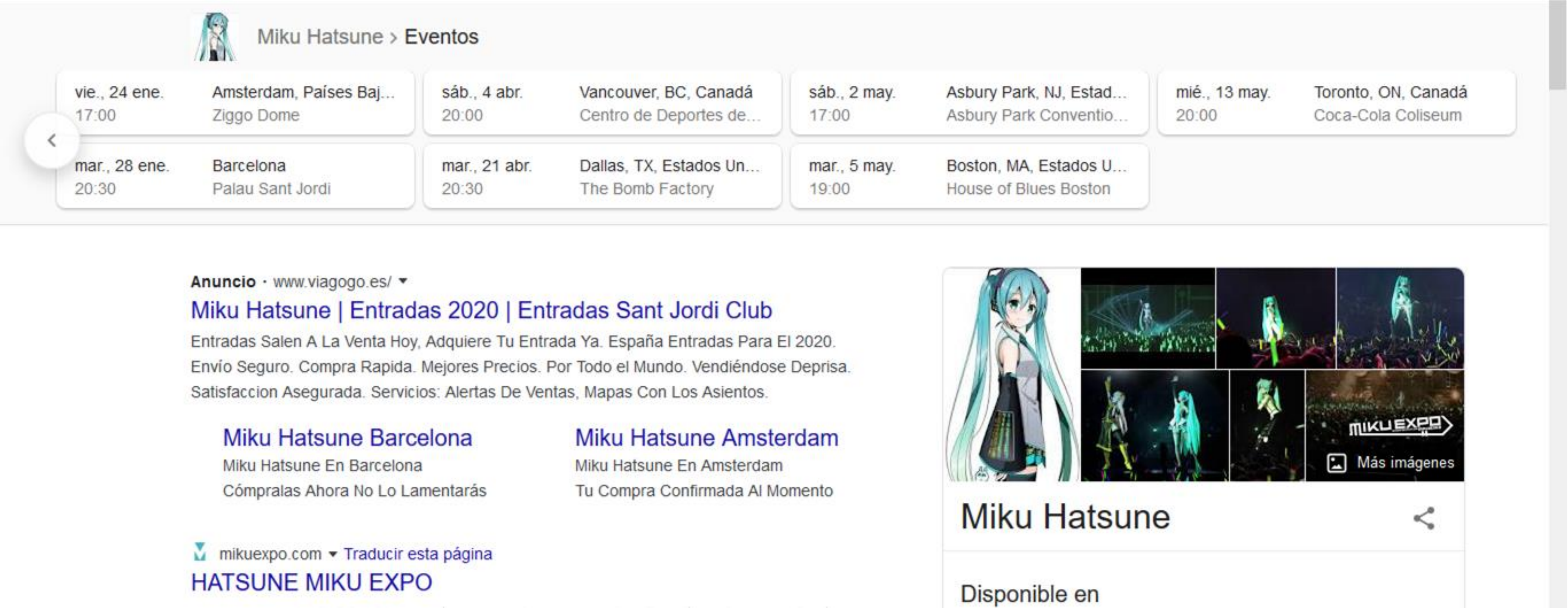
- **Motivation**
- Interdisciplinarity and diversity
- Selected projects

Assessing the impact of AI on human behaviour

Hatsune Miku

https://www.youtube.com/watch?v=dhYaX01NOfA



Kondo "marries" a moving, talking hologram

https://en.wikipedia.org/wiki/Hatsune_Miku

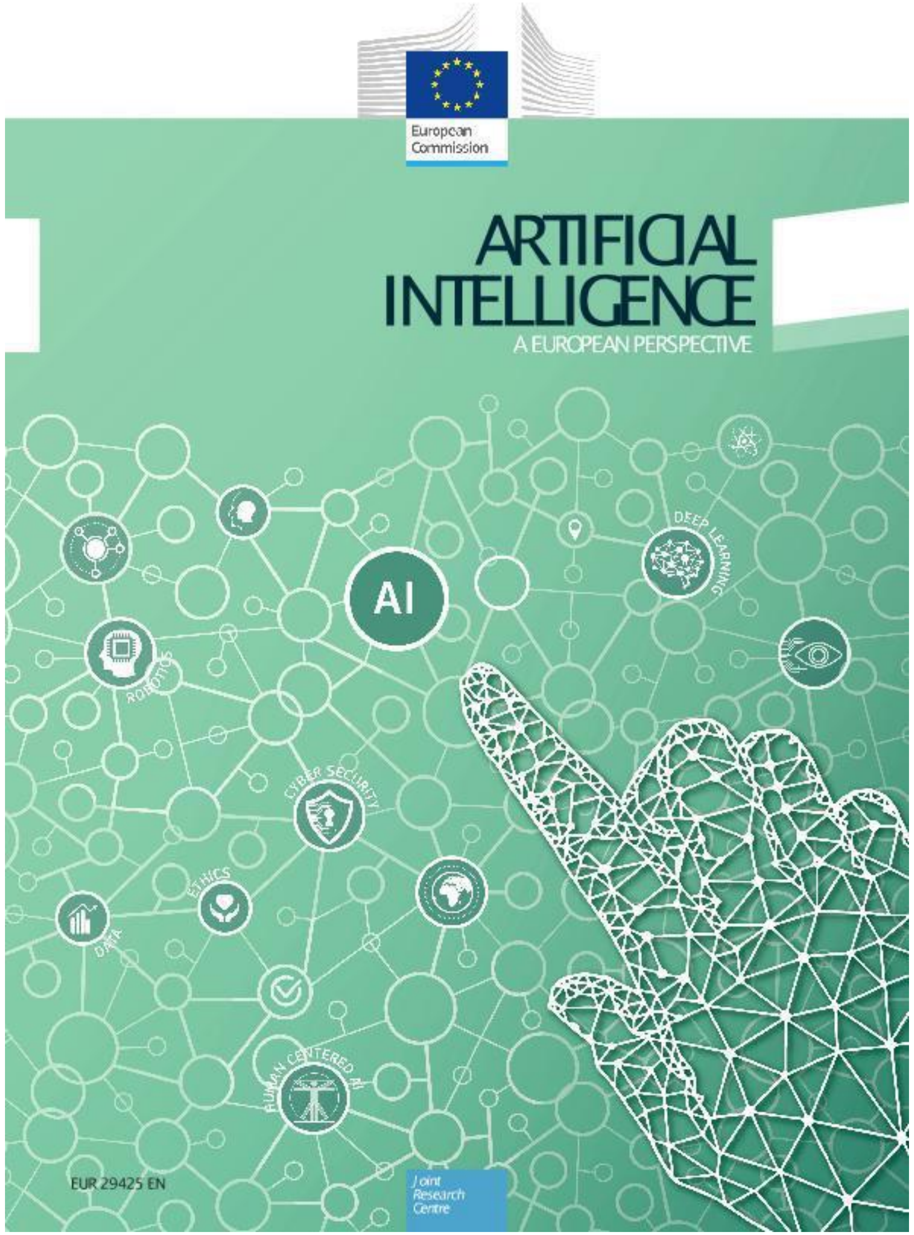
the japan times

https://www.youtube.com/watch?v=dtu4t_Zc3d4

Artificial Intelligence

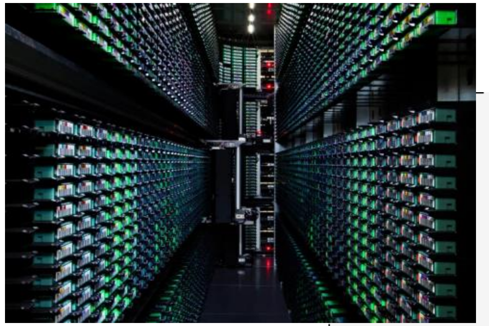
Machines or agents capable of observing its environment and taking decisions towards a certain goal

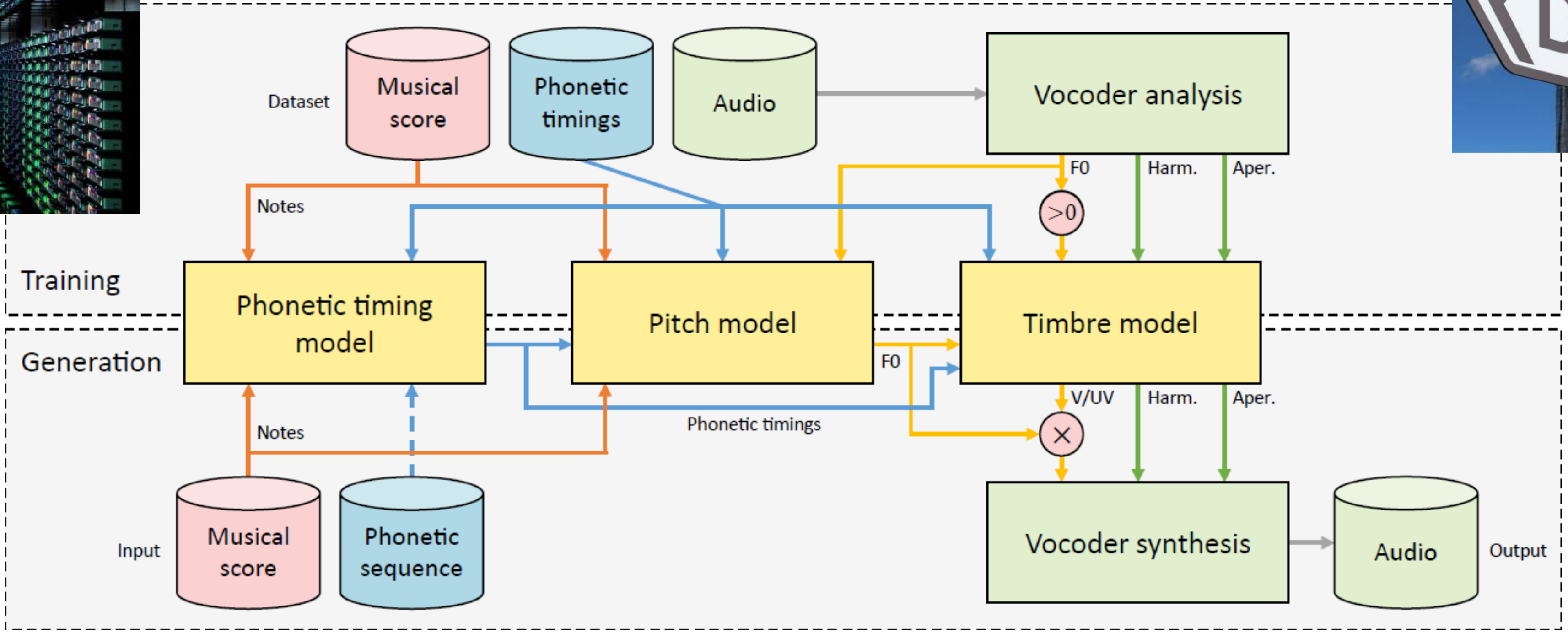
- Machine learning: data+computation+algorithms
  - General purpose (GPT)
  - Scalable, personalization
  - Address cognitive tasks



Artificial Intelligence: A European Perspective. Joint Research Centre, 2018.
https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/artificial-intelligence-european-perspective

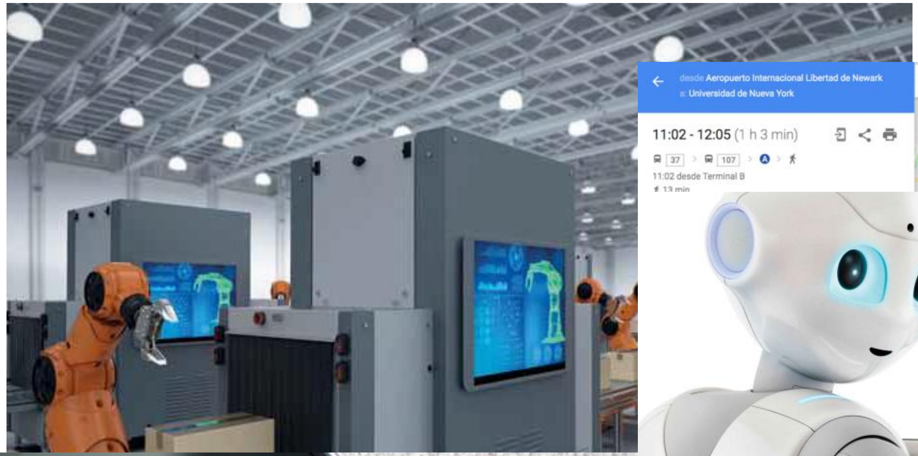
Deep learning method, data-driven

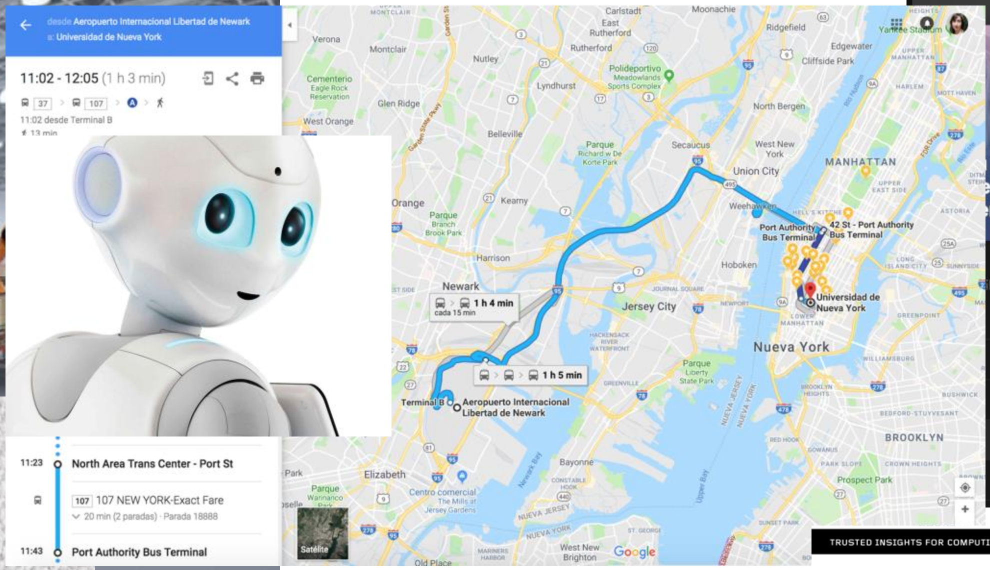


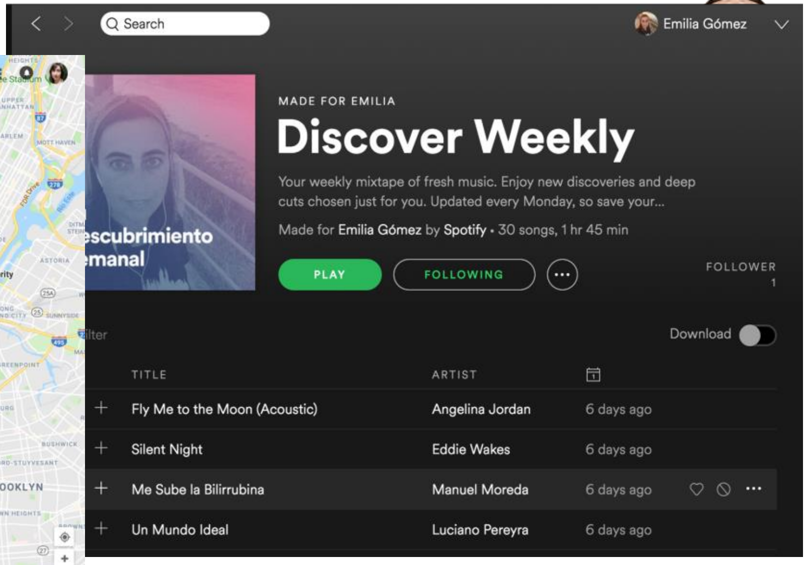


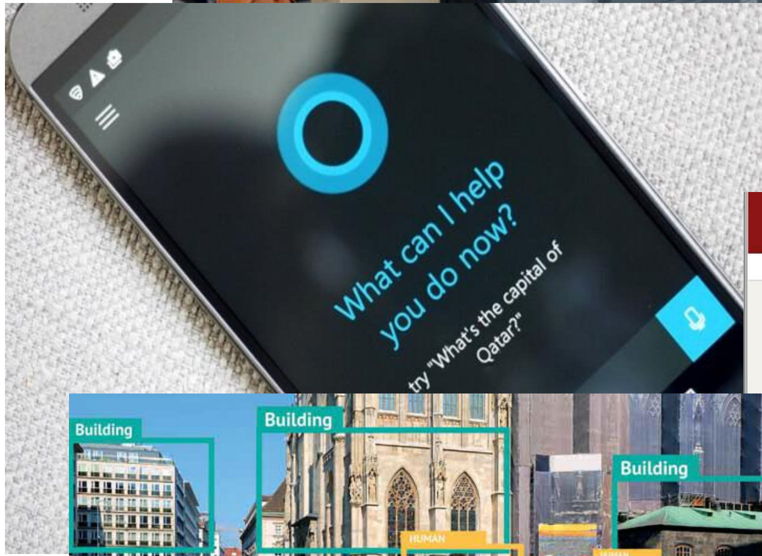
Blaauw, M., and Bonada, J. A Neural Parametric Singing Synthesizer, Interspeech, 2017 https://mtg.github.io/singing-synthesis-demos/

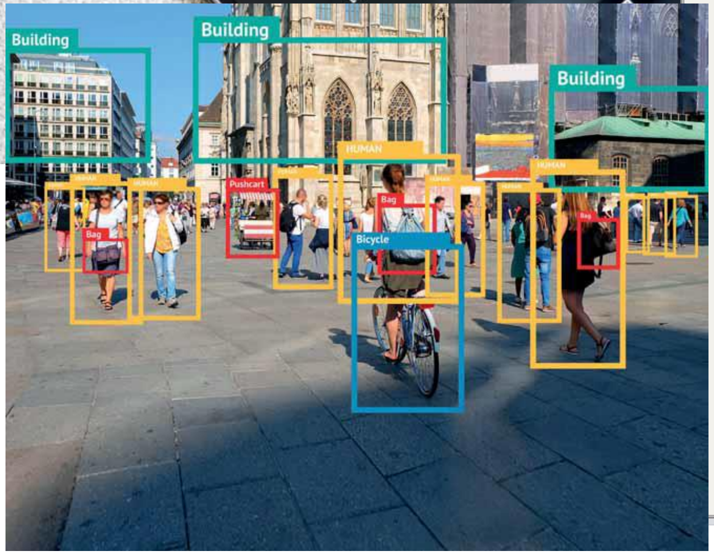
Gómez, Blaauw, Bonada, Chandna, Cuesta. Deep Learning for Singing Processing: Achievements, Challenges and Impact on Singers and Listeners, Keynote talk, ICML Workshop on ML and Music, 2018 arxiv.org/abs/1807.03046

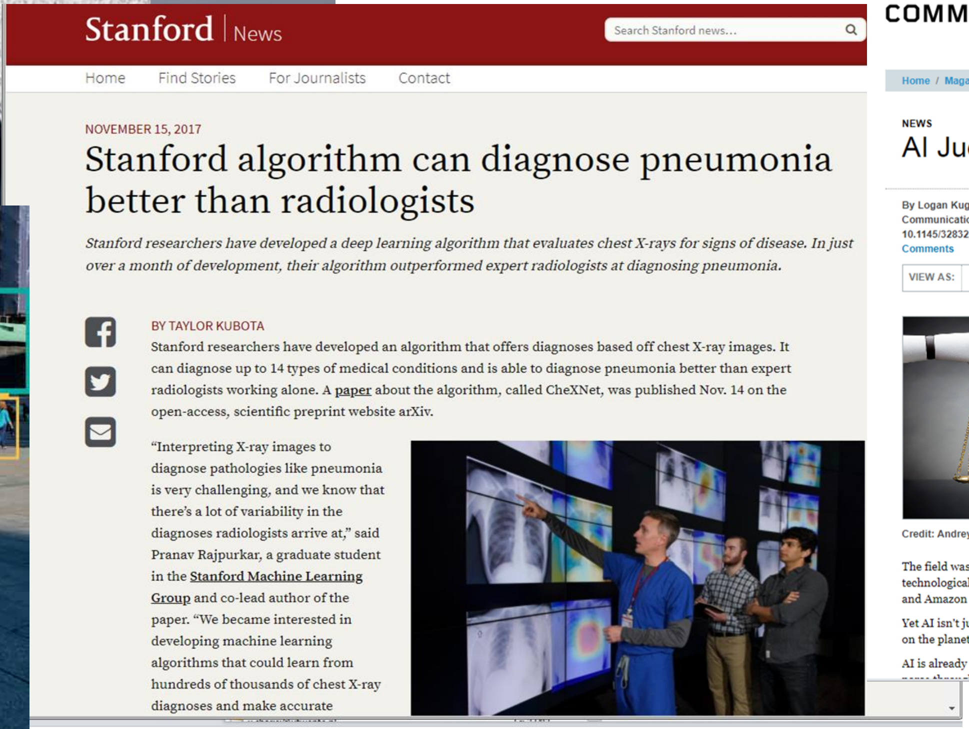












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NOVEMBER 15, 2017

Stanford algorithm can diagnose pneumonia better than radiologists

Stanford researchers have developed a deep learning algorithm that evaluates chest X-rays for signs of disease. In just over a month of development, their algorithm outperformed expert radiologists at diagnosing pneumonia.

BY TAYLOR KUBOTA

Stanford researchers have developed an algorithm that offers diagnoses based off chest X-ray images. It can diagnose up to 14 types of medical conditions and is able to diagnose pneumonia better than expert radiologists working alone. A paper about the algorithm, called CheXNet, was published Nov. 14 on the open-access, scientific preprint website arXiv.

"Interpreting X-ray images to diagnose pathologies like pneumonia is very challenging, and we know that there's a lot of variability in the diagnoses radiologists arrive at," said Pranav Rajpurkar, a graduate student in the Stanford Machine Learning Group and co-lead author of the paper. "We became interested in developing machine learning algorithms that could learn from hundreds of thousands of chest X-ray diagnoses and make accurate

COMMUNICATIONS OF THE ACM

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NEWS

AI Judges and Juries

By Logan Kugler
Communications of the ACM, December 2018, Vol. 61 No. 12, Pages 19-21
10.1145/3283222

Credit: Andrey Popov

When the head of the U.S. Supreme Court says artificial intelligence (AI) is having a significant impact on how the legal system in this country works, you pay attention. That's exactly what happened when Chief Justice John Roberts was asked the following question:

"Can you foresee a day when smart machines, driven with artificial intelligences, will assist with courtroom fact-finding or, more controversially even, judicial decision-making?"

His answer startled the audience.

"It's a day that's here and it's putting a significant strain on how the judiciary goes about doing things," he said, as reported by *The New York Times*.

In the last decade, the field of AI has experienced a renaissance. The field was long in the grip of an "AI winter," in which progress and funding dried up for decades, but technological breakthroughs in AI's power and accuracy changed all that. Today, giants like Google, Microsoft, and Amazon rely on AI to power their current and future profit centers.

Yet AI isn't just affecting tech giants and cutting-edge startups; it is transforming one of the oldest disciplines on the planet: the application of the law.

AI is already used to analyze documents and data during the legal discovery process, thanks to its ability to

Technology impact assessment

1. Who are the people affected?
2. Who are the ‘winners’ (benefit), who the ‘losers’ (cost)?
3. How many lives can be saved?
4. How much money/jobs can be saved?
5. What are the short-term and long-term costs/benefits?

Human behaviour and machine intelligence

Provide cognitive assistance:
"computer-assisted".

Affect decision making and cognitive and socio-emotional capabilities.

GOALS

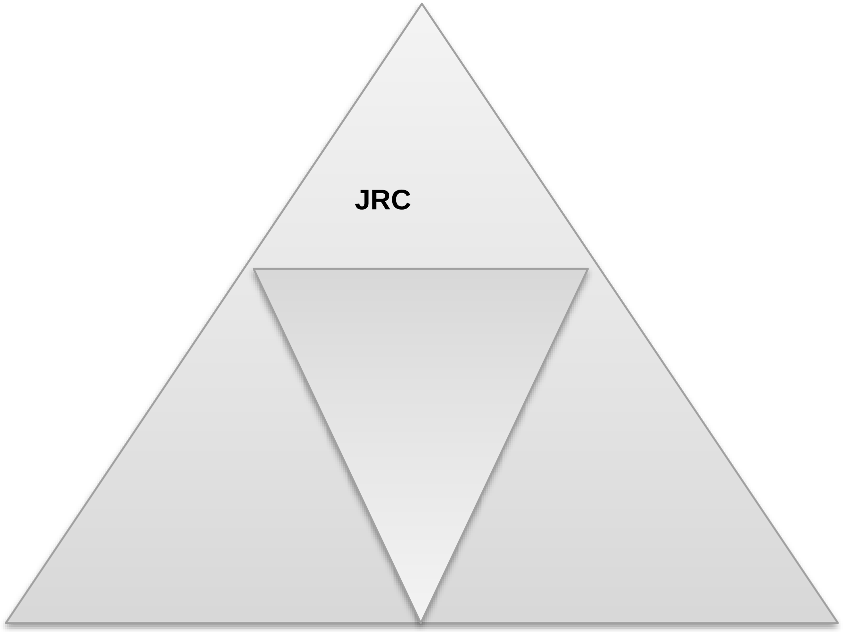
Find the right balance

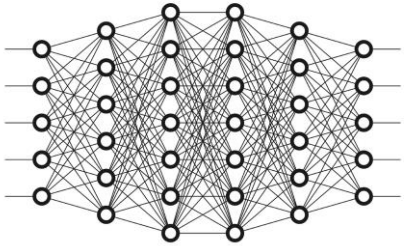
Best strategies for human-AI ~~competition~~ cooperation == human-centered AI

HUMAINT key research principles

1. **Interdisciplinary**

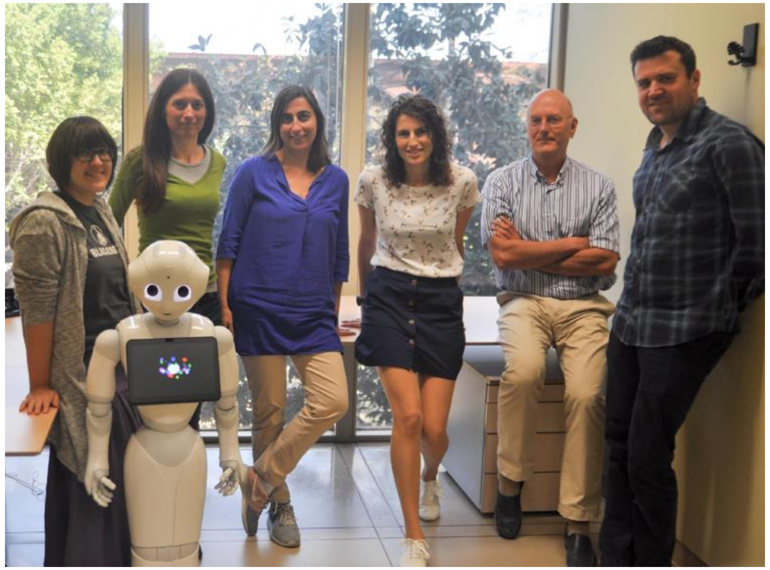
Human behaviour





Machine learning

Economics of AI



HUMAINT key research principles

1. Interdisciplinary
2. **Impact**

Human behaviour

We publish **open, reproducible research**
We provide policy support

Machine learning

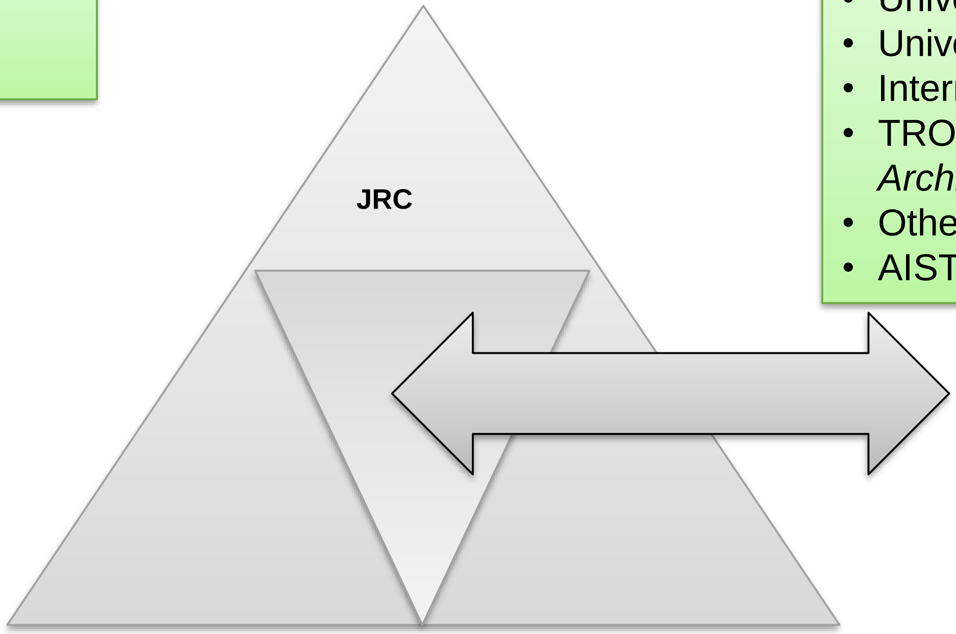
Economics of AI

HUMAINT key research principles

1. Interdisciplinary
2. Impact
3. **Community**

- 8 associated external fellows
- Universidad Pablo Olavide
- Unviersidad de Sevilla
- Universidad Politécnica de Valencia
- University of Cambridge
- International Consortium for Socially Intelligent Robotics
- TROMPA (*Towards Richer Online Music Public-domain Archives*) H2020 project
- Other JRC units and DGs of the EC
- AIST Japan, Honda Research Institute

Human behaviour



Research community

Machine learning

Economics of AI

Outline

- Motivation
- **Interdisciplinarity and diversity**
- Selected projects

This summary is based on the work by Barry, A., Born, G., and Weszkalnys, G. Logics of interdisciplinarity. Economy and Society Volume 37 Number 1 February 2008:20-49

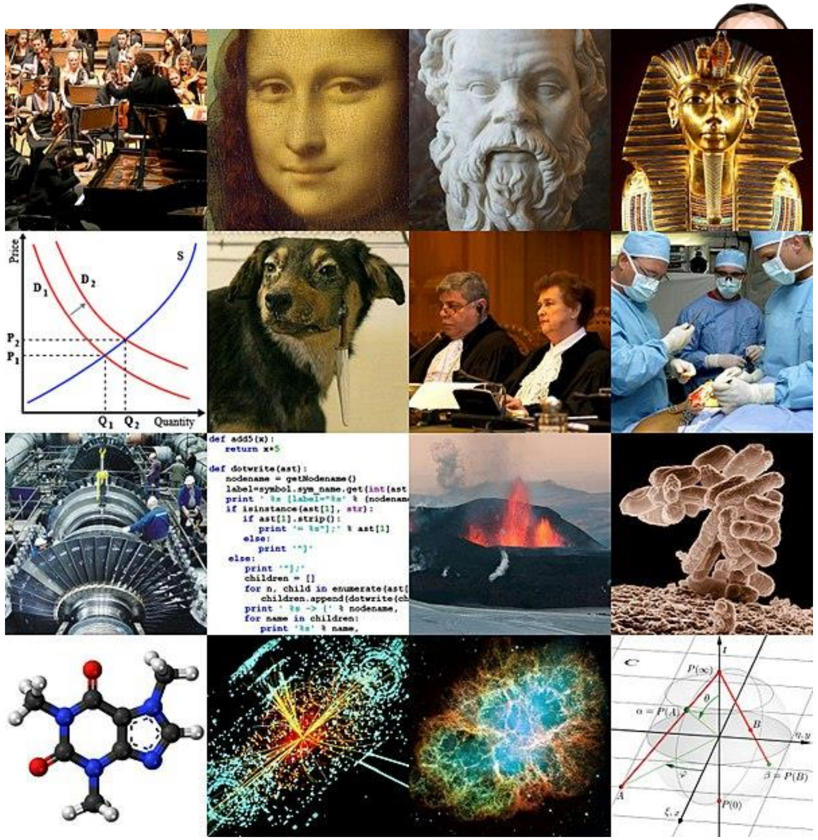
Disciplines discipline disciples

A commitment to a discipline is a way of

ensuring that certain disciplinary methods and concepts are used rigorously

and that

undisciplined and undisciplinary objects, methods and concepts are ruled out.



https://ia.wikipedia.org/wiki/File:Academic_disciplines_(collage).jpg

Barry, A., Born, G., and Weszkalnys, G. Logics of interdisciplinarity . Economy and Society Volume 37 Number 1 February 2008:20-49

Why interdisciplinarity?

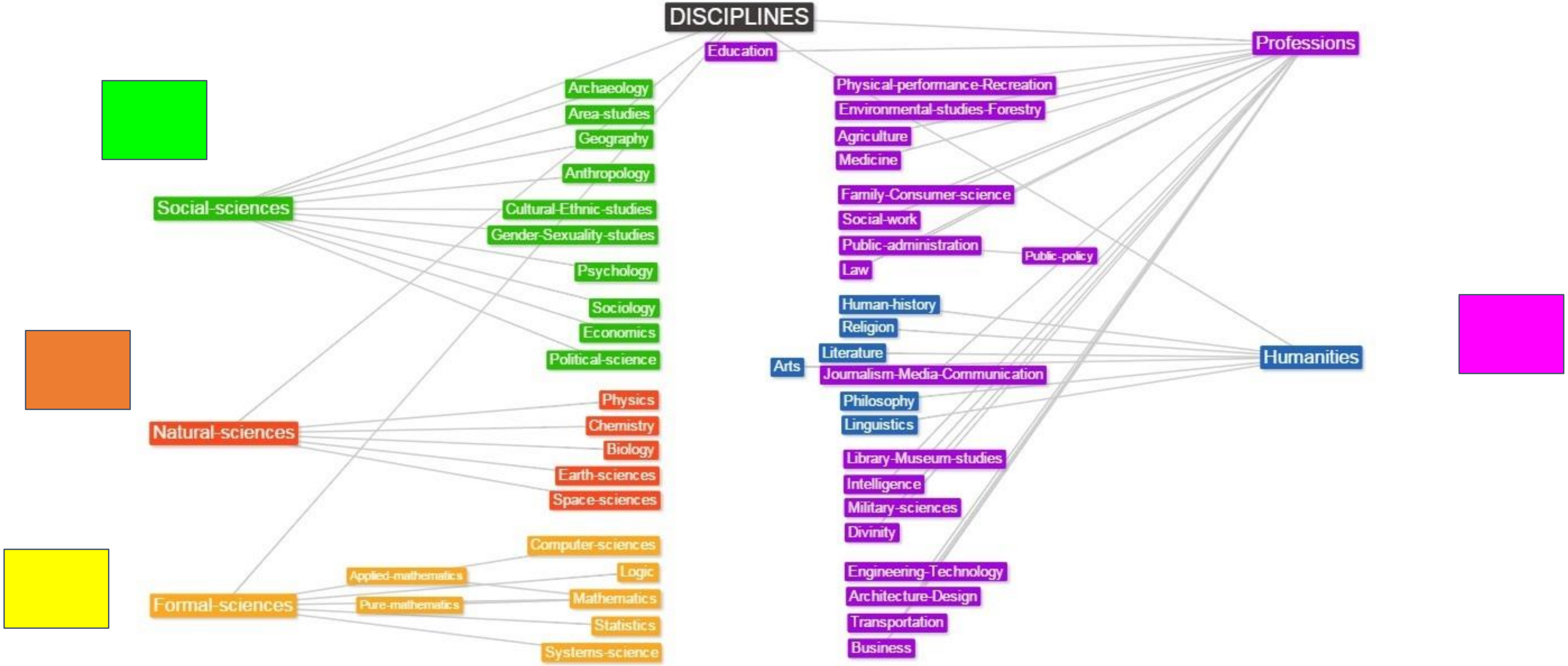
1. Accountability

1. Innovation and economic growth

2. Ontology: affect ontological change.

Barry, A., Born, G., and Weszkalnys, G. Logics of interdisciplinarity . Economy and Society Volume 37 Number 1 February 2008:20-49

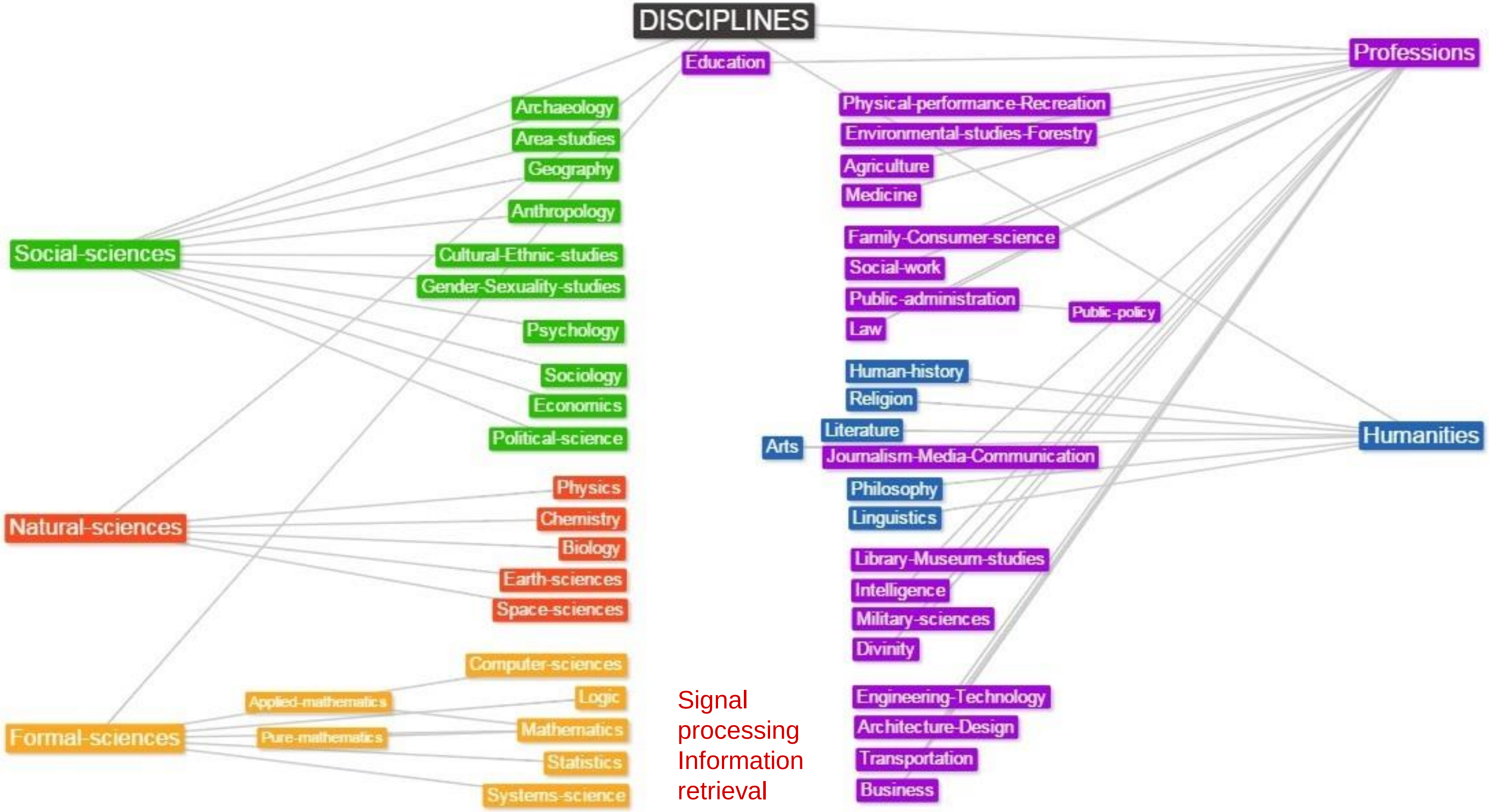
What is your main discipline?



Copy and edit your own interdisciplinarity sheet https://tinyurl.com/tuknmd5

https://upload.wikimedia.org/wikipedia/commons/7/7c/Disciplines_mind_map.jpg

My main discipline



Signal
processing
Information
retrieval

https://upload.wikimedia.org/wikipedia/commons/7/7c/Disciplines_mind_map.jpg

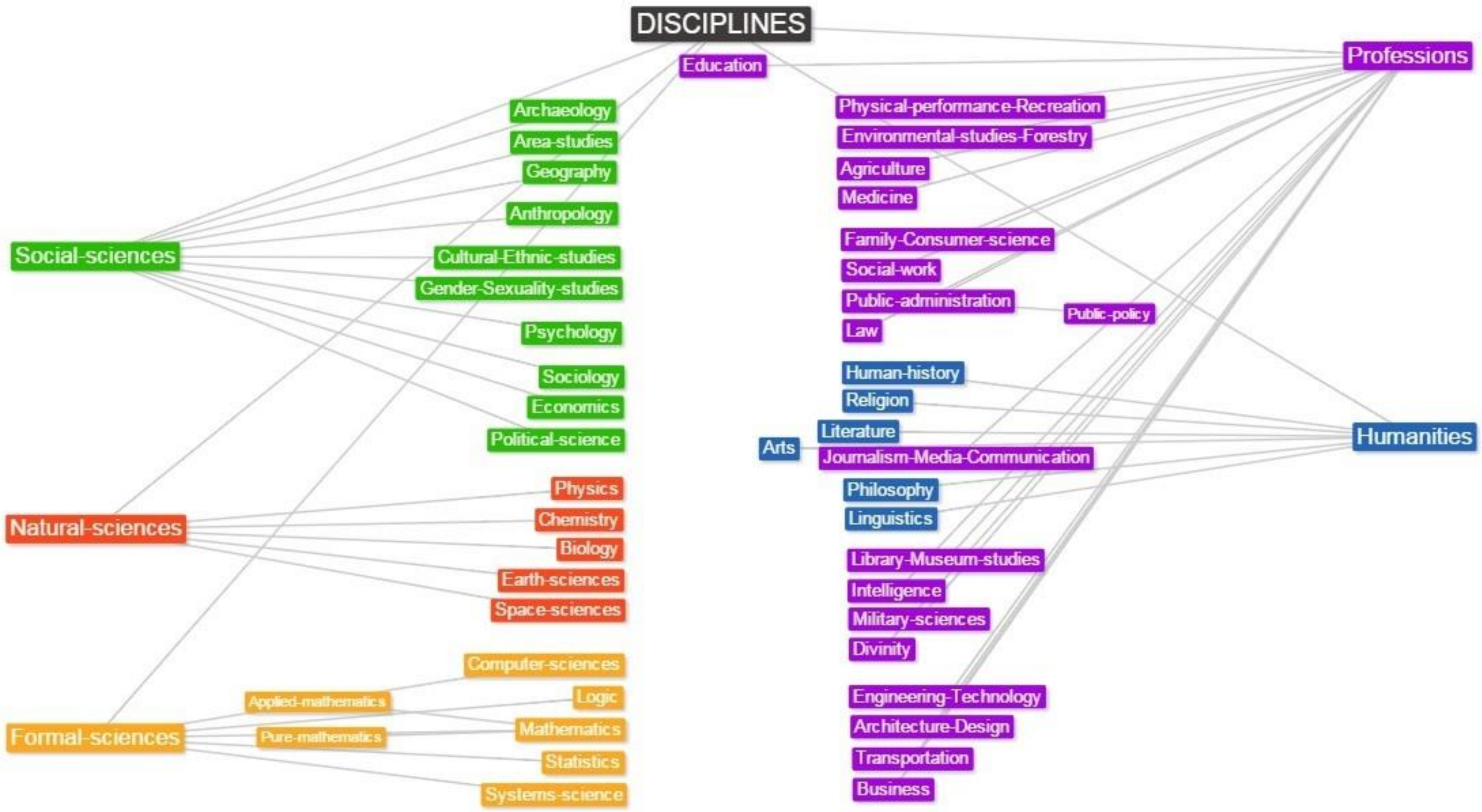
Beyond disciplines

- Boundary transgressions
- Solution to a series of contemporary problems.
- New model of knowledge production: new forms of quality control (Nowotny, Scott and Gibbons, 2001)

https://www.flickr.com/photos/frauleinschiller/5612922237

Barry, A., Born, G., and Weszkalnys, G. Logics of interdisciplinarity . Economy and Society Volume 37 Number 1 February 2008:20-49

Can you identify several disciplines in your work?



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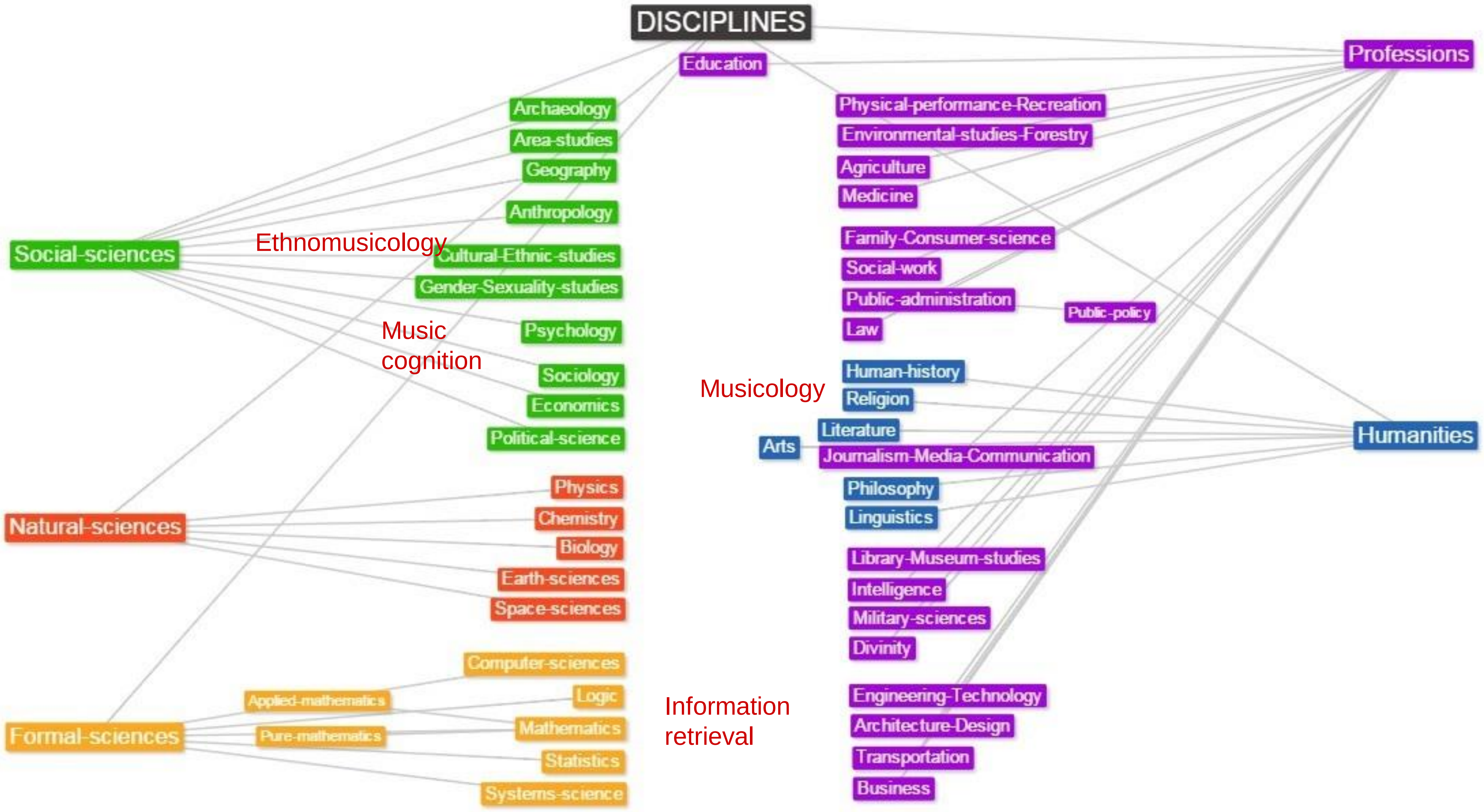
My main disciplines



https://upload.wikimedia.org/wikipedia/commons/7/7c/Disciplines_mind_map.jpg

Modes and logics of interdisciplinary

Interdisciplinarity is not historically novel BUT there is a new sense that it is a need to better connect research & society/economy.

Methodology (Barry, Born and Weszkalnys, 2008)

- Internet-based mapping survey of interdisciplinary fields.
- Selected fields:
  a. Environmental and climate change research
  b. Ethnography in the IT industry
  c. Art-science
- 10 case studies of initiatives in these fields across different national settings.

Barry, A., Born, G., and Weszkalnys, G. Logics of interdisciplinarity . Economy and Society Volume 37 Number 1 February 2008:20-49

Concepts

1. Multidisciplinarity
    - Several disciplines **cooperate** but remain unchanged, working with standard disciplinary framings.

2. Interdisciplinarity
    - Integrate or **synthesize** perspectives from several disciplines.

3. Transdisciplinary
    - Transgression, **fusion**.
    - Oriented to the complexity of real-world problem solving, overcoming distance between specialized and lay knowledges or between research and policy.

Barry, A., Born, G., and Weszkalnys, G. Logics of interdisciplinarity . Economy and Society Volume 37 Number 1 February 2008:20-49

Modes of interdisciplinarity

1. Integrative-synthesis: integration of disciplines in relatively symmetrical form.
    - Example: synthesis of disciplines via “universal” mathematical models: climate change research integrating natural scientific and social scientific accounts for impact.

1. Subordination-service: master vs service discipline.
    - Example: art to communicate science, science as a service to art (providing resources and equipment for a project conceived in artistic term).

1. Agonistic-antagonistic: criticism to transcend historical disciplines into new ones.
    - Example: ethnography in the IT industry as an opposition to previous sociological approaches to the study of technology or to scientific approaches to study technologies.

Barry, A., Born, G., and Weszkalnys, G. Logics of interdisciplinarity . Economy and Society Volume 37 Number 1 February 2008:20-49

Modes of interdisciplinarity & methodologies

1. Integrative-synthesis

1. Subordination-service

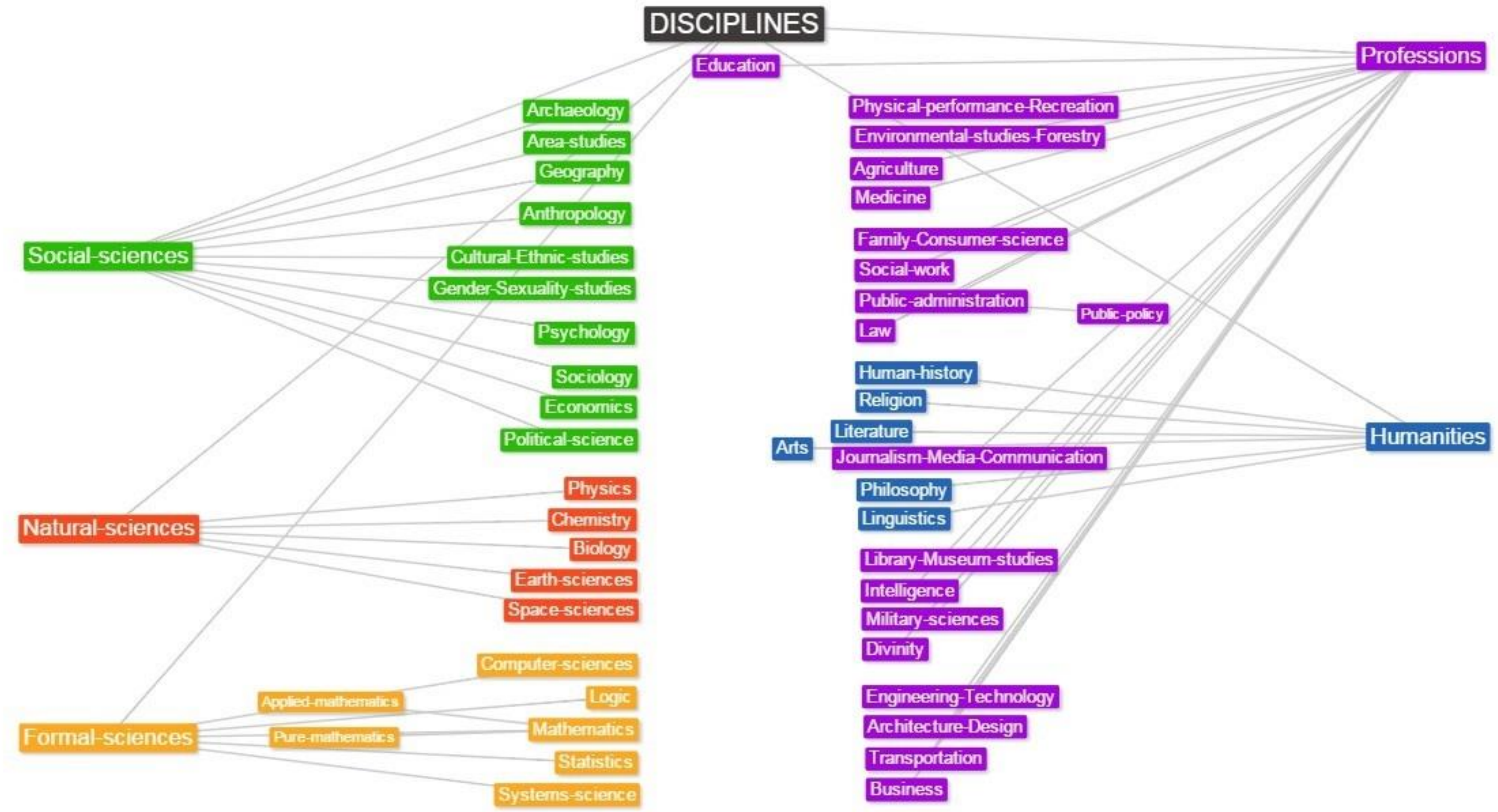
1. Agonistic-antagonistic

Methodological orientations

- Problem-solving, policy orientation in response to new problems/objects.
- Practice-oriented, labour division.

Barry, A., Born, G., and Weszkalnys, G. Logics of interdisciplinarity . Economy and Society Volume 37 Number 1 February 2008:20-49

Can you identify modes of interdisciplinarity or methodologies?



https://upload.wikimedia.org/wikipedia/commons/7/7c/Disciplines_mind_map.jpg

Diversity

Fostering diversity, AI systems should be accessible to all, regardless of any disability, and involve relevant stakeholders throughout their entire life circle.

- Interdisciplinarity is a particular aspect of diversity.
- Valued for incorporating different views in the design process.
- Diversity is difficult to conceptualize.
  - Disciplines
  - Cultural background
  - Gender
  - ...

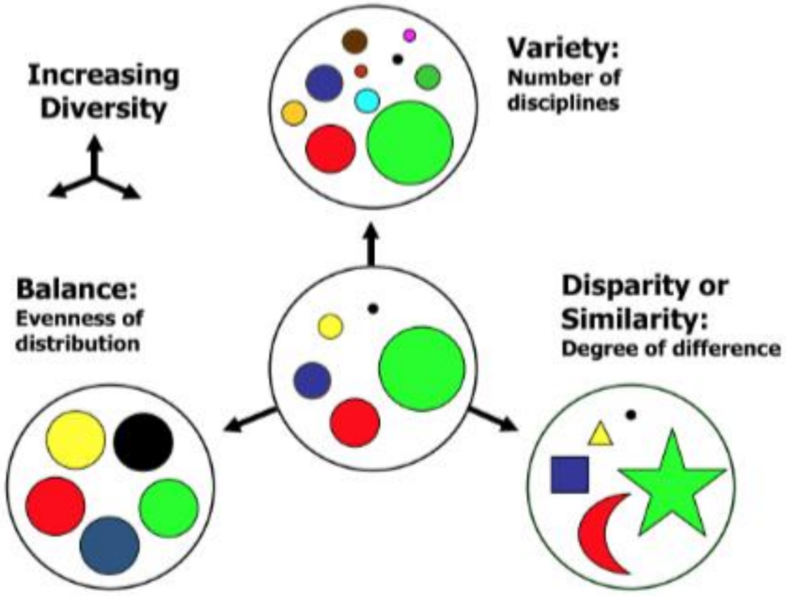


Figure 1: Schematic representation of the attributes of diversity, in the context of interdisciplinary analysis, from (Rafols and Meyer 2010).

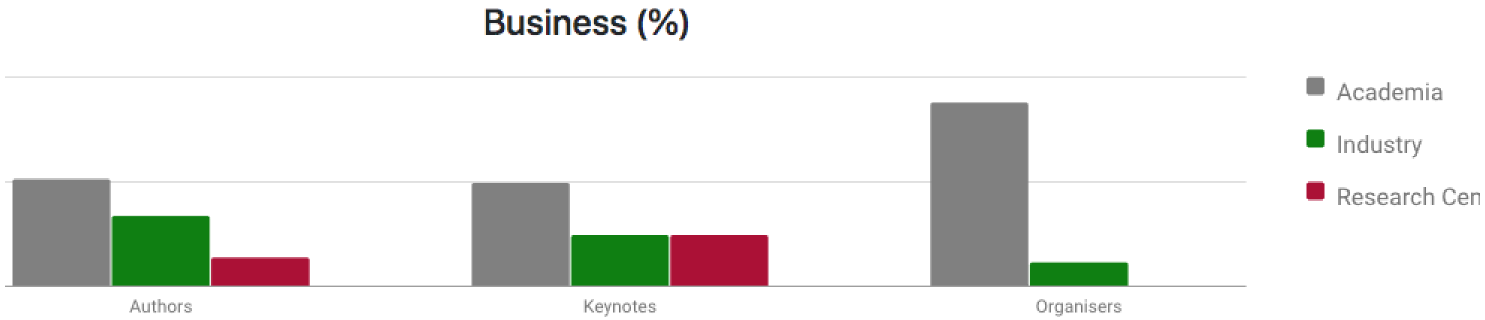
Freire, A., Porcaro, L., Gómez, E. Measuring Diversity of Artificial Intelligence Conferences, arxiv.

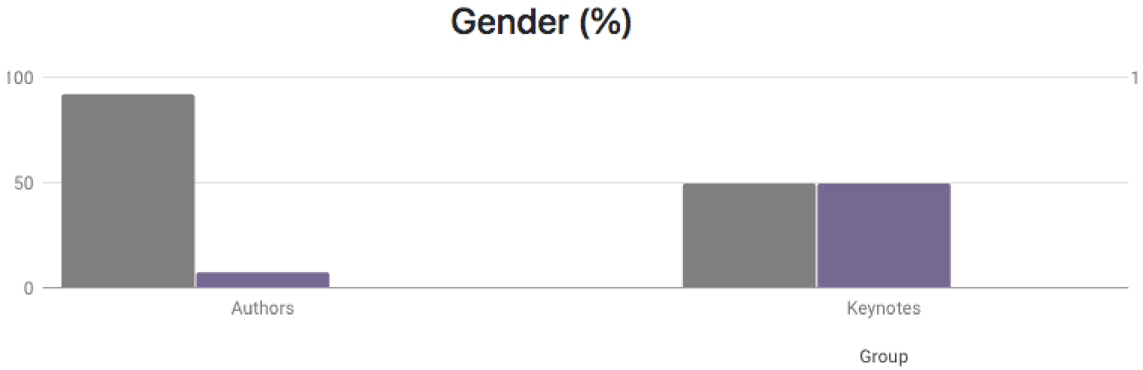
divinAI (divinAI.org)

- Collaborative project: Universitat Pompeu Fabra, Joint Research Centre, welcoming contributors
- Study how diverse are AI conference, related to AI geo-politics
- Define a set of indicators derived from biodiversity (Pielou, Shannon Index).
  - Gender
  - Geographical origin, institution (culture)
  - Focus (academia vs industry)
- Monitor the distribution, evolution, impact of diversity policies.
- Hackfest Barcelona 31st, New York February 10th

Freire, A., Porcaro, L., Gómez, E. Measuring Diversity of Artificial Intelligence Conferences, arxiv.

ICML 2017





divinai.org
Universitat Pompeu Fabra, Barcelona, Jan 31st
AAAI diversity & inclusion activities, New York

Take-home messages

- Benefits of interdisciplinary approaches to address societal problems.
- Interdisciplinarity takes many forms.
- Not easy to achieve transdisciplinarity: vocabulary, methods, quality standards.
- Has practical risks.
- Link with diversity of communities.

Policy making questions

1. How can AI affect human decision making? e.g. recidivism prediction
2. How does social robots affect children development?
3. How will AI impact jobs and workplaces?
4. Which dual use can have AI in medicine/healthcare?
5. How will recommender systems impact opinion/culture?

Outline

- Motivation
- Interdisciplinarity and diversity
- **Selected projects**

HUMAINT research topics

1. Decision making
2. Child-robot interaction
3. AI and EU labour markets
4. Medicine and healthcare
5. Music

HUMAINT research topics

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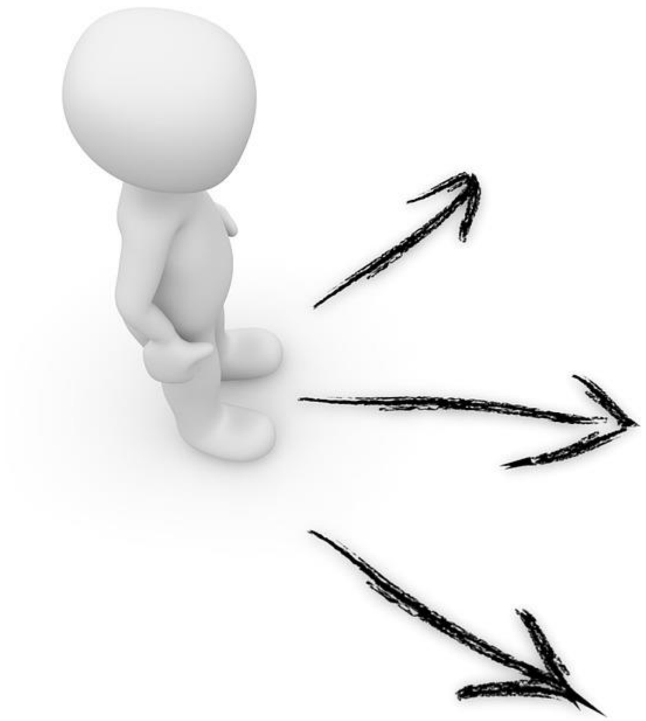
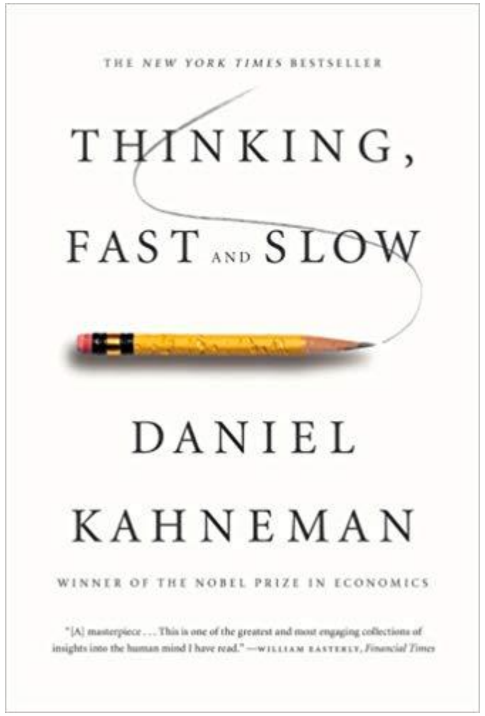
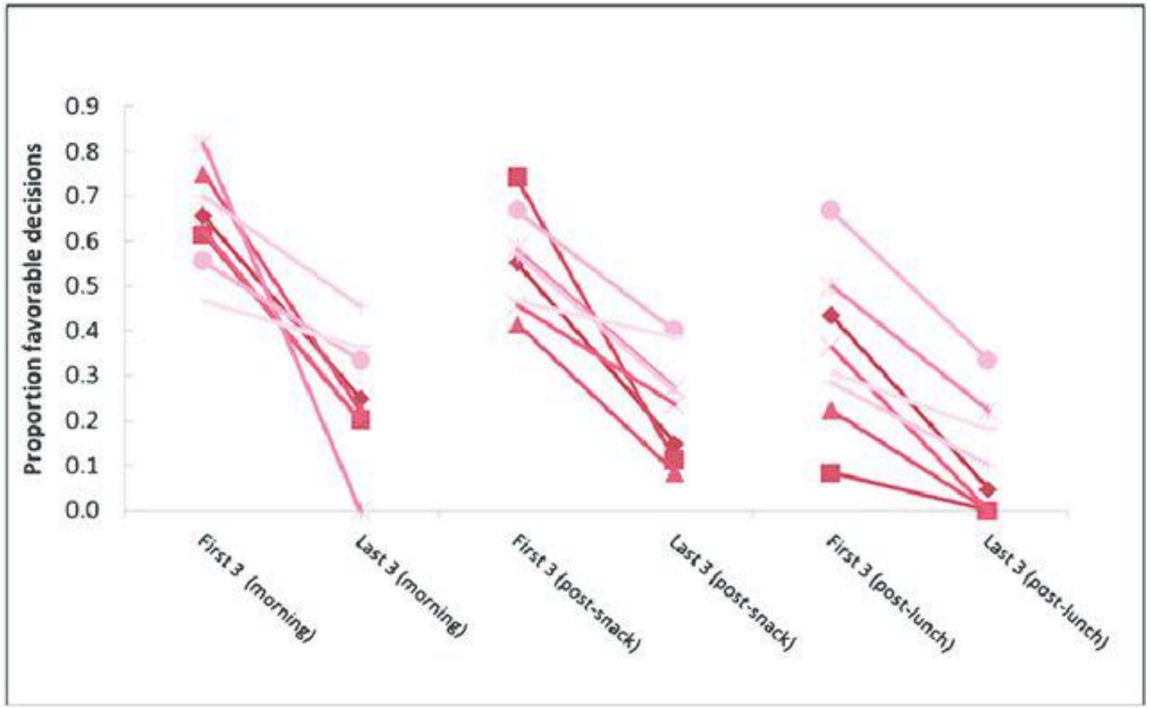


Tolan, S., Miron, M., Castillo, C., Gómez, E. "Why Machine Learning May Lead to Unfairness in Juvenile Justice: Evidence from Catalonia", ICAIL 2019.

Decision making: humans

- Humans are prone to cognitive biases (Kahheman, 2011)
- Judge decisions can be affected by hunger or mood (Dazinger et al., 2011; Chen et al., 2016)





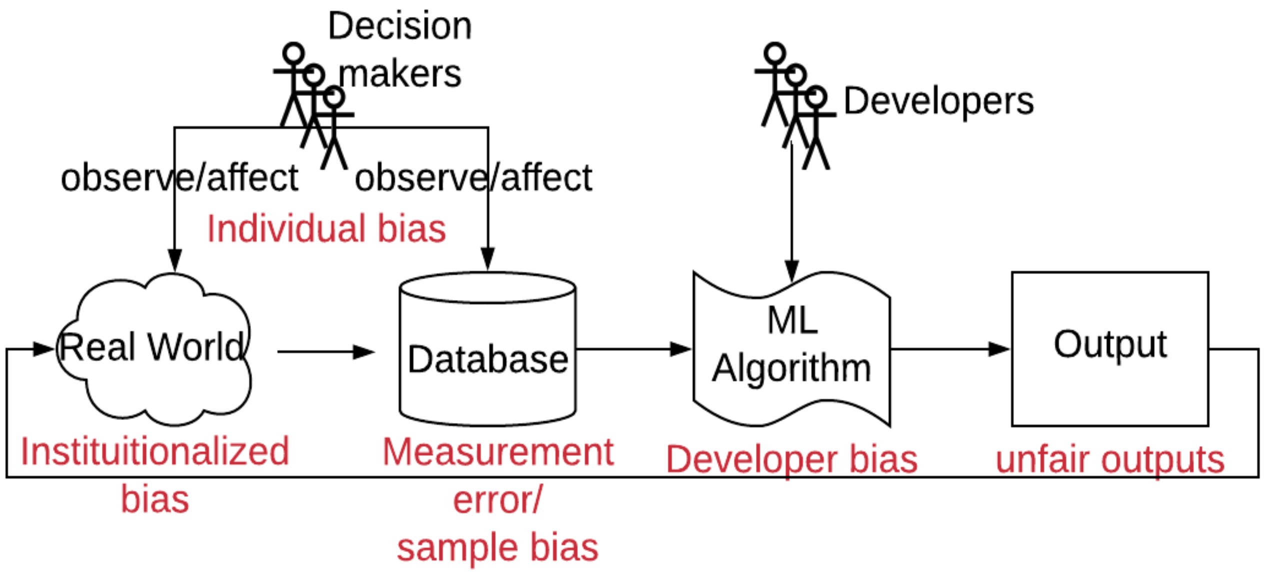
Tolan, S. (2018). Fair and Unbiased Algorithmic Decision Making: Current State and Future Challenges, JRC technical report.

Bias, fairness, discrimination

- Bias: systematic deviation from truth, a feature of statistical models (Metcalf, 201).
- Fairness: a feature of value judgments (Metcalf, 2019)
- Discrimination: a legal concept based on group membership
  sex, race, colour, ethnic and social origin, political opinion, membership of a national minority, property, birth, disability, age or sexual orientation
  (Article 14, European Convention on Human Rights)

Decision making: ML algorithms

- Support the formalization of decision making process
- Not neutral, may learn human biases (Barocas and Selbs, 2016; Angwin et al., 2016)
- Reliance, liability & responsibility



Tolan, S. (2018). Fair and Unbiased Algorithmic Decision Making: Current State and Future Challenges, JRC technical report.

Decision making: humans vs algorithms

1. Data on human decision making
2. Model, evaluate and understand: predictive performance and group fairness* (human and interpretable ML models)
3. Design best cooperation strategies

- Task: binary classification

Juvenile recidivism

* Computer science researchers talk of at least 21 definitions of fairness

Decision making: humans vs algorithms

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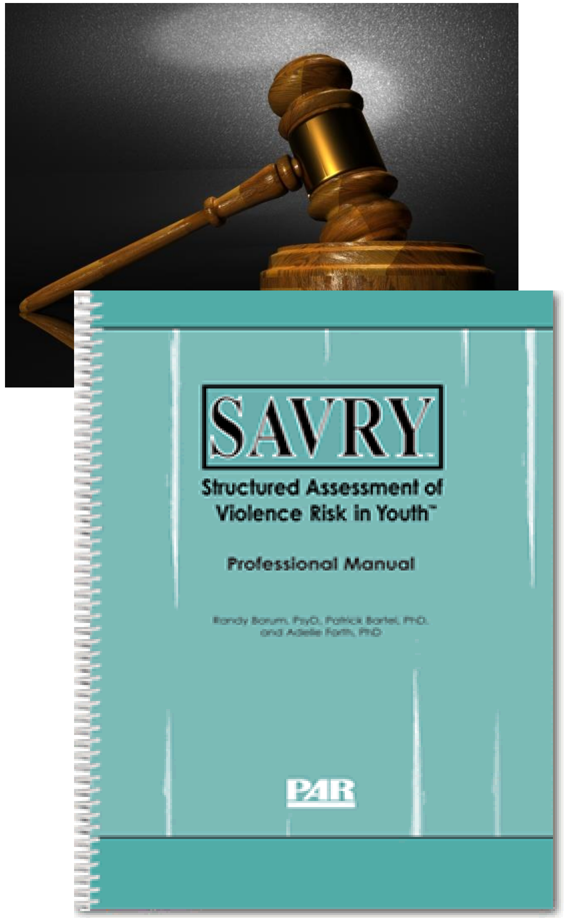

- Task: binary classification
- SAVRY: structured professional **risk** assessment framework (24 risk factors, final assessment)
- Dataset originated in Catalonia (4752 defendants, 2002-2010, recidivism 2013-2015, 855 SAVRY assessment).
- Antonio Pueyo (Universitat de Barcelona), Carlos Castillo (Universitat Pompeu Fabra)

Tolan, S., Miron, M., Castillo, C., Gómez, E. "Why Machine Learning May Lead to Unfairness in Juvenile Justice: Evidence from Catalonia", ICAIL 2019.
Borum, R. 2006. Manual for the structured assessment of violence risk in youth (SAVRY). (2006).

Decision making: humans vs algorithms

- Machine Learning improves predictive performance
- BUT may lead to unfairness…
- Algorithms emphasize correlations (base rates)

Static features: defendant demographics and criminal history
SAVRY scores: expert assessment (24)

ML: logistic regression (logit), multi-layer perceptron (mlp), support vector machine with a linear (lsvm) or radial (rsvm) kernel, K-nearest neighbors (knn), random forest (rf), and naive bayes (nb)

Figure 3: Comparison of group fairness metrics in terms of nationality. The reference group are Spanish nationals.

Tolan, S., Miron, M., Castillo, C., Gómez, E. "Why Machine Learning May Lead to Unfairness in Juvenile Justice: Evidence from Catalonia", ICAIL 2019.

Decision making: humans vs algorithms

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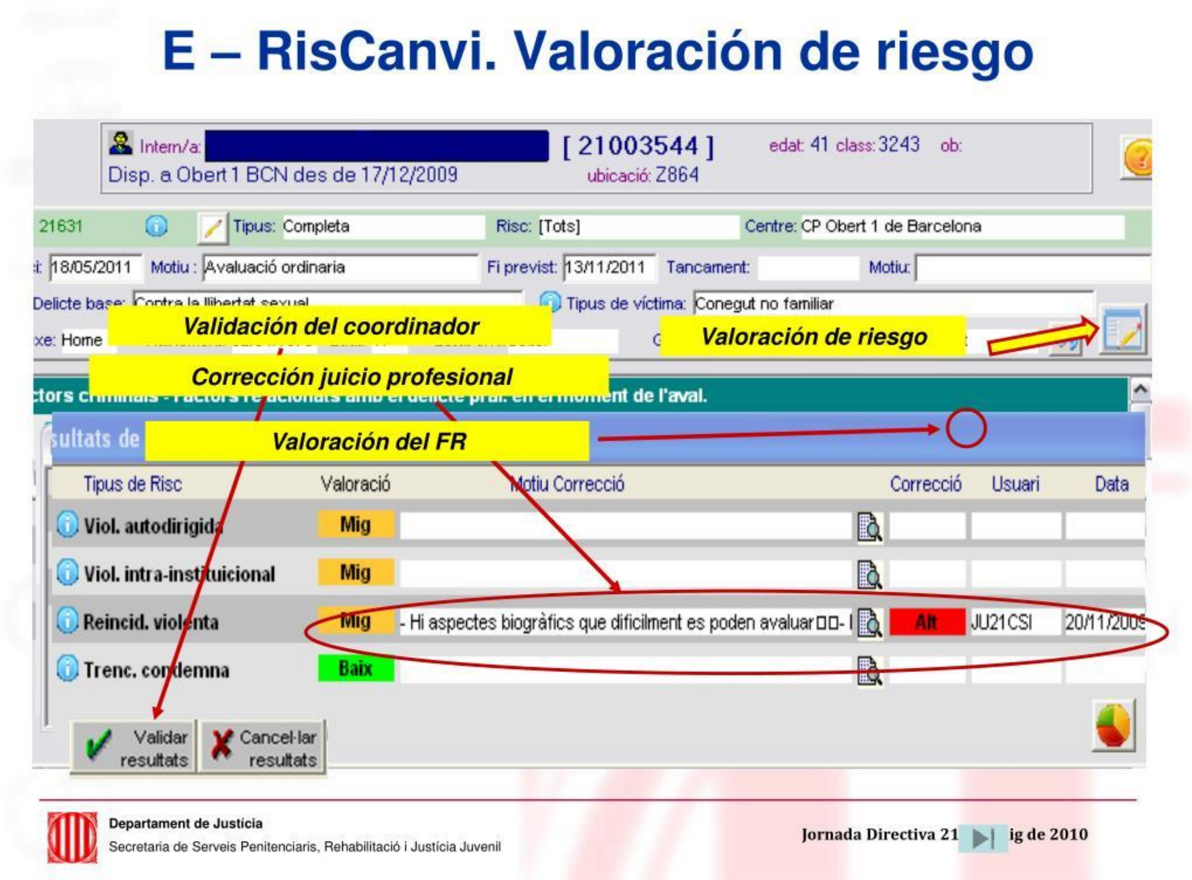
Figure 2: Comparison of group fairness metrics using sex as the protected attribute. The reference group are men.

Tolan, S., Miron, M., Castillo, C., Gómez, E. "Why Machine Learning May Lead to Unfairness in Juvenile Justice: Evidence from Catalonia", ICAIL 2019.

Algorithm-supported decision making

- Data limited, specially in sensitive and complex scenarios.
- Developers must understand the social context in which the algorithm will be embedded (Selbst et al. 2019).
- Domain experts and users must understand the algorithmic approach (transparency).
- Strategies for algorithm-human cooperation: over-reliance, algorithm corrections.



Interdisciplinarity sheet

Disciplines			
Mode of interdisciplinarity	**Integrative synthesis**	**Subordination service**	**Agonistic antagonistic**
Methodological orientations	**Problem-solving**	**Practice-oriented**	**Other**

Interdisciplinarity sheet

Other disciplines	• Computer Science, mathematics (formal sciences) • Psychology (social sciences) • Sociology (social sciences) • Law (humanities)		
Mode of interdisciplinarity	**Integrative synthesis**	**Subordination service**	**Agonistic antagonistic** Fair Machine Learning
Methodological orientations	**Problem-solving** Evaluation	**Practice-oriented** Recidivism prediction	**Other**

HUMAINT research topics

1. Decision making
2. **Child-robot interaction**
3. AI and EU labour markets
4. Medicine and healthcare
5. Music

Charisi, V., Alcorn, A. M., Kennedy, J., Johal, W., Baxter, P., and Kynigos, C. (2018). The Near Future of Children’s Robotics. In Proceedings of the 17th ACM Conference on Interaction Design and Children (IDC ’18). ACM, New York, NY, USA,

Child-Robot Interaction

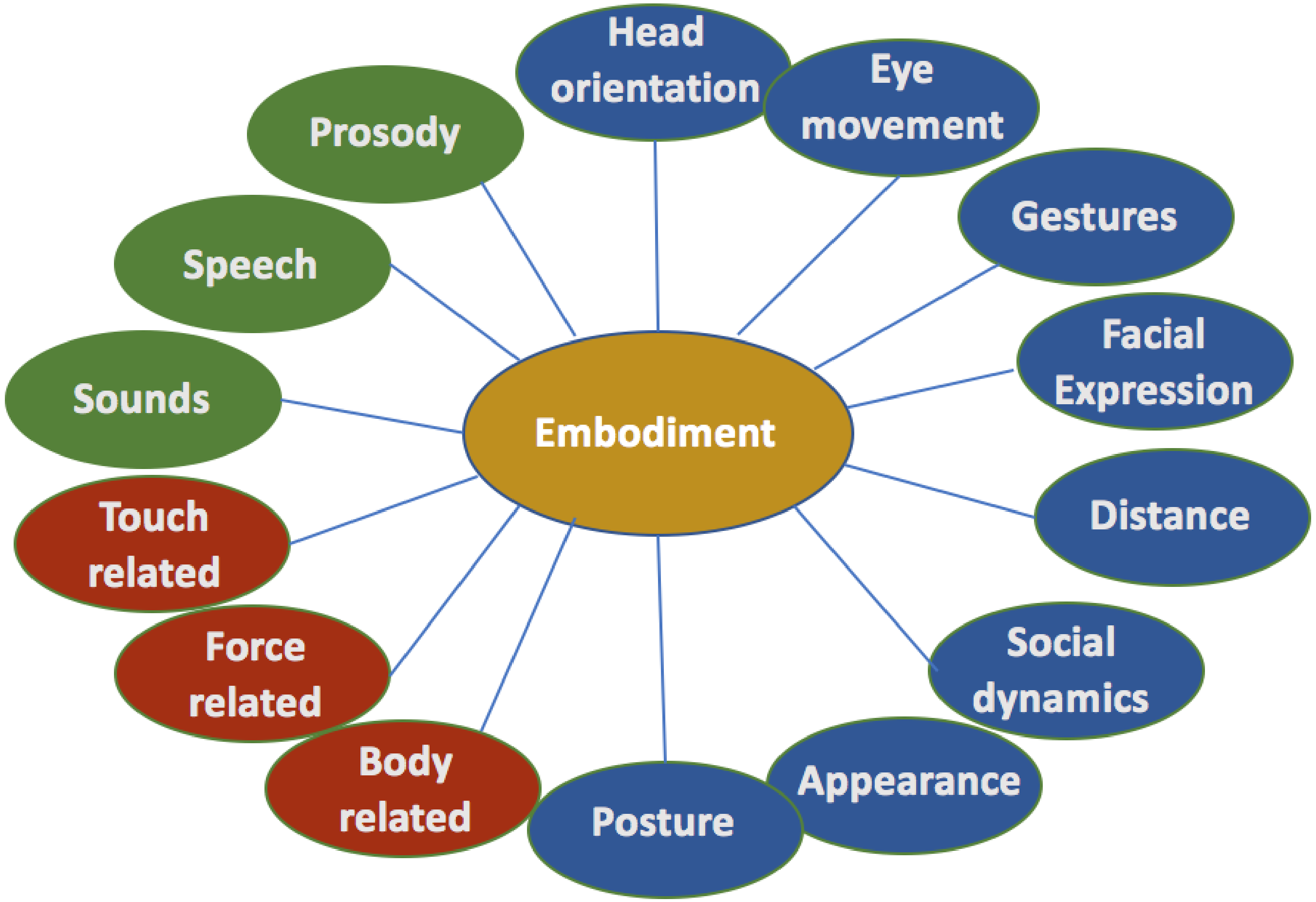
- Social robots = embodied AI

Charisi, V., Alcorn, A. M., Kennedy, J., Johal, W., Baxter, P., and Kynigos, C. (2018). The Near Future of Children’s Robotics. In Proceedings of the 17th ACM Conference on Interaction Design and Children (IDC ’18). ACM, New York, NY, USA,

Human-robot interaction: disciplines

Disciplines

- Embodied Social AI
- AI (Machine learning)
- Robotics
- Psychology
- Philosophy

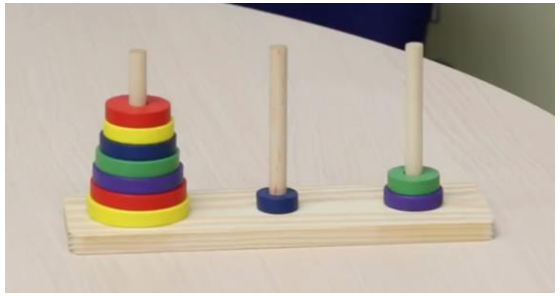


Charisi, V., Sabanovic, S., Thill, S., Gomez, E., Nakamura, K., & Gomez, R. (2019). Expressivity for Sustained Human-Robot Interaction. In 2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)(pp. 675-676). IEEE.

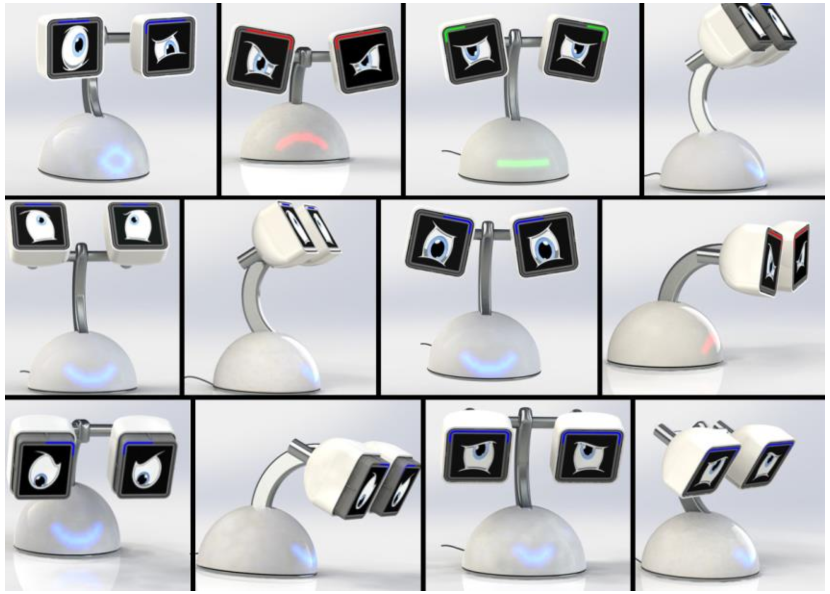
Child-robot interaction: approach

1. Behavioural studies: problem solving, social interaction, emotional engagement
2. Qualitative & quantitative understanding
3. Experiment and design interaction strategies and contribute to system design

- Task: tower of Hanoi
- 5-8 y.o. children
- Social robot



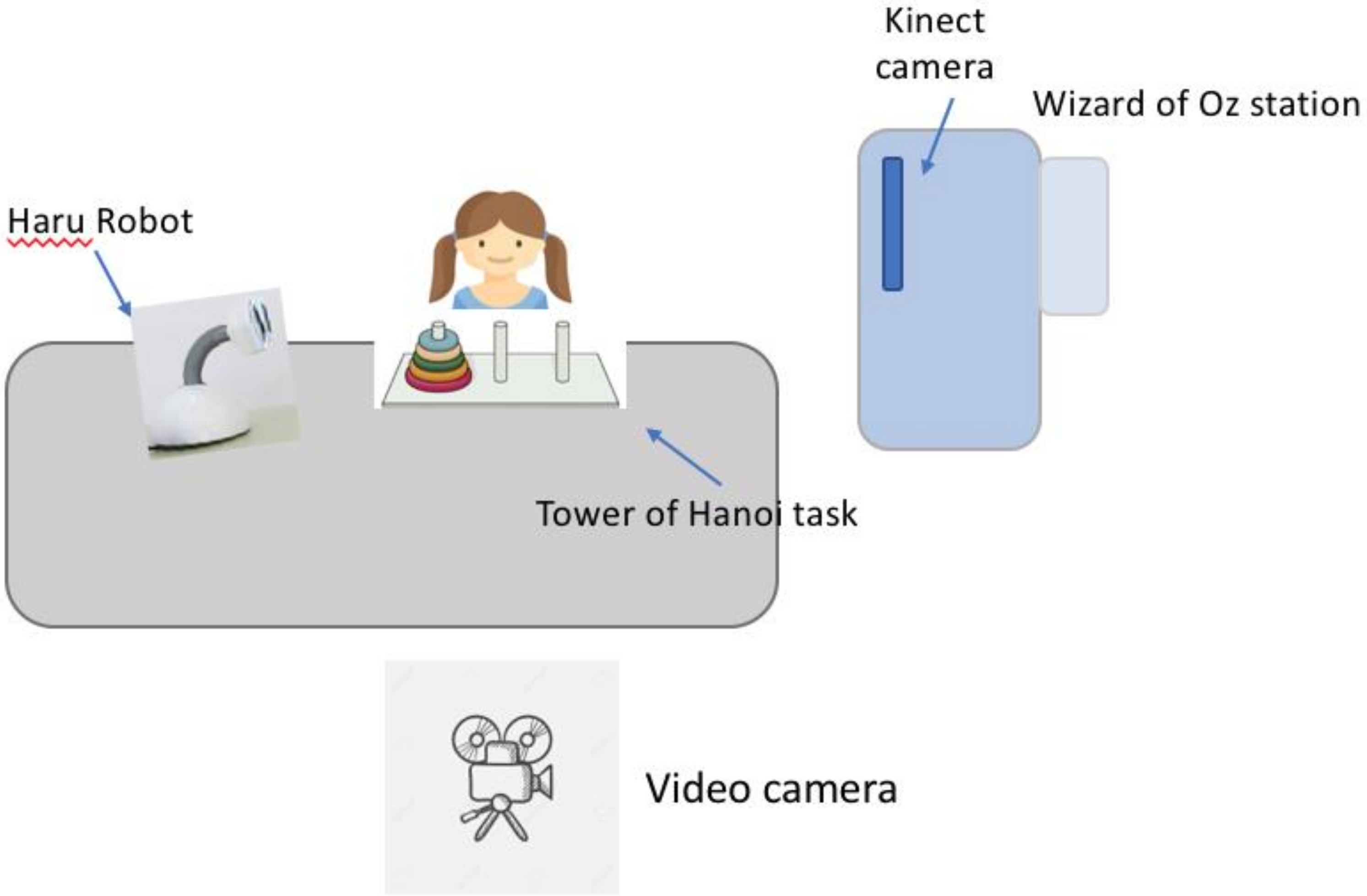
(Lucas,1883)



Gómez, R. Haru: Hardware Design of an Experimental Tabletop Robot Assistant, HRI2018

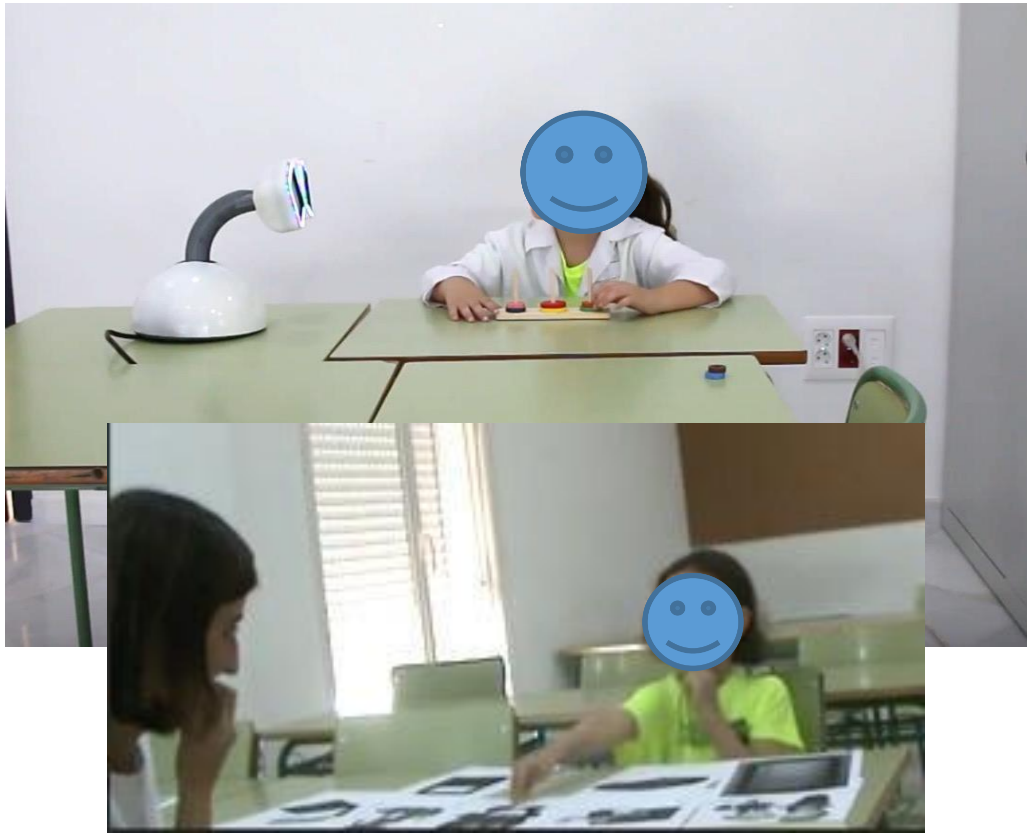
Child-robot interaction: approach

- Study 1
- What is the impact of Social Robot Interventions on <u>children's learning process</u>?



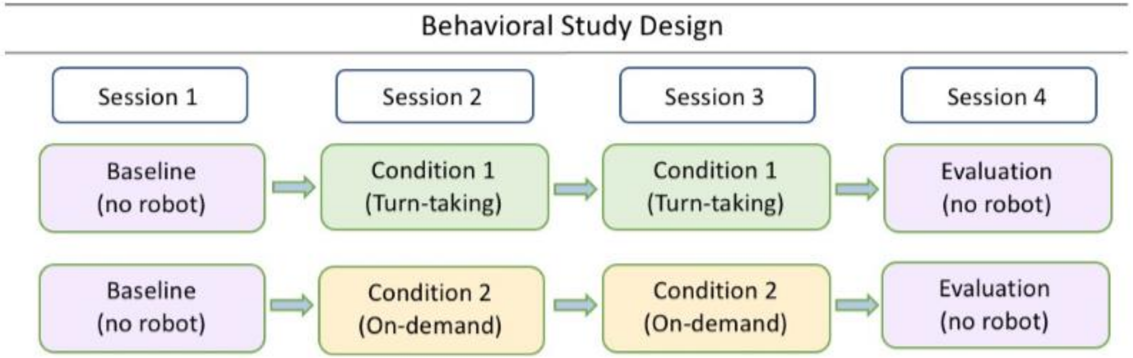
Charisi, V., Gómez, E., Mier, G., Merino, L., Gomez, R. 2020. Child-Robot Collaborative Problem-Solving and the Importance of Child's Voluntary Interaction: A Developmental Perspective. In press.

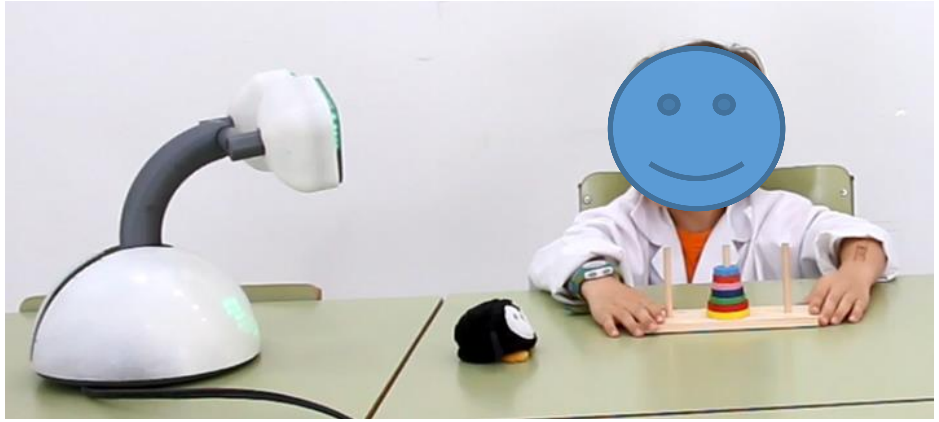
Child-robot interaction: approach



Methodology

- 72 sessions of 15 min, 113 tasks from 20 children.

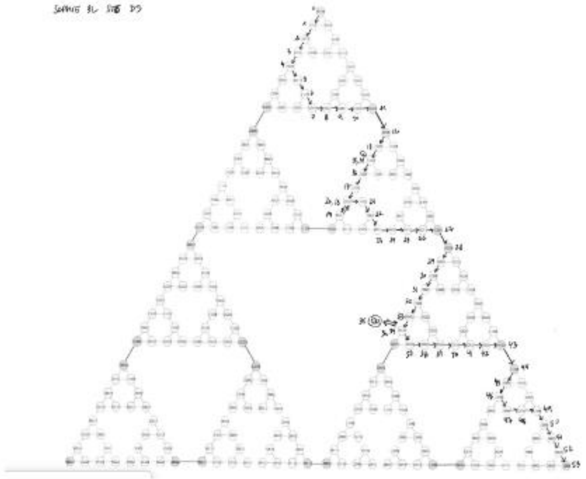




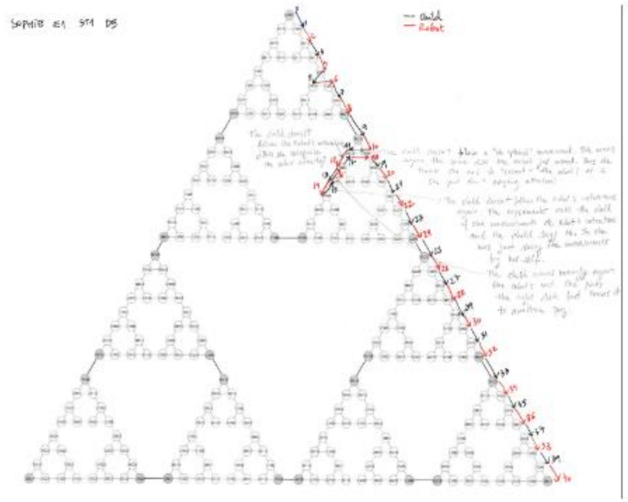
Charisi, V., Gómez, E., Mier, G., Merino, L., Gomez, R. 2020. Child-Robot Collaborative Problem-Solving and the Importance of Child's Voluntary Interaction: A Developmental Perspective. In press.

Results

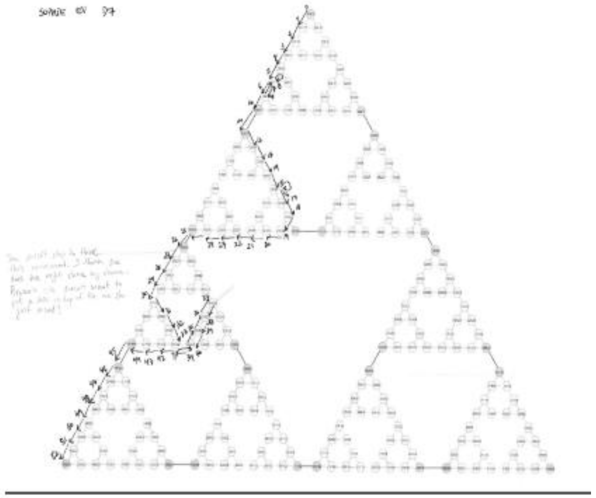
- Need for exploration
- Importance of self-initiated interaction
- Individual differences
- Learning process



Sophie BL D5



Sophie E1 D5



Sophie EV D5

Charisi, V., Gómez, E., Mier, G., Merino, L., Gomez, R. 2020. Child-Robot Collaborative Problem-Solving and the Importance of Child's Voluntary Interaction: A Developmental Perspective. In press.

Ethical considerations with children

Research ethics

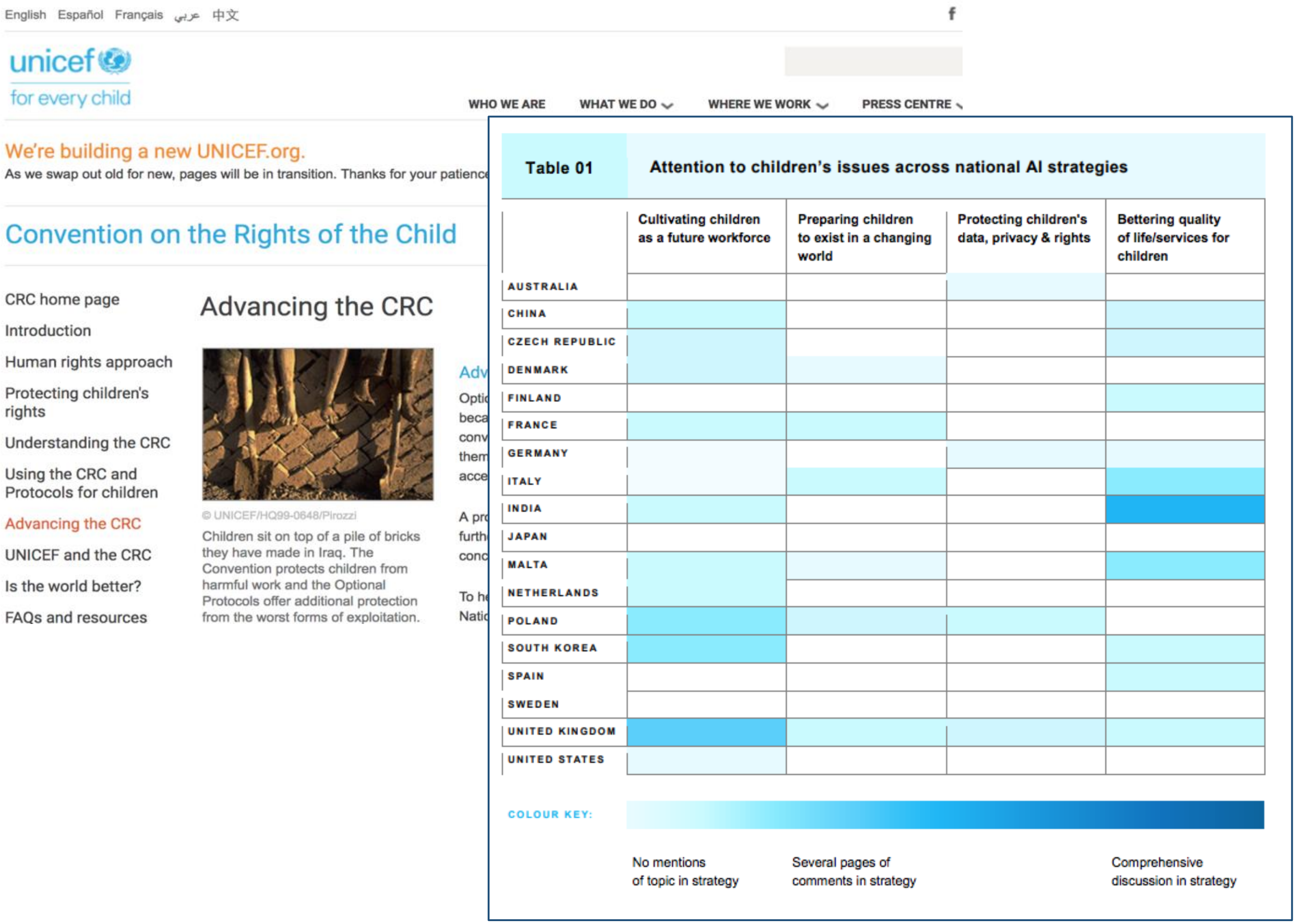
What

Transparency
Privacy
Consistency
Explainability
Inclusion
Deception

Responsible design and innovation

- How does research affect the paradigms in **formal education and informal learning**?
- How will **industry** of Children’s Toys and Media_be aligned with the Child’s Values and Rights?
- How can we **embed Child’s Values and Rights** into our systems?

Ethical considerations: what



Priorities

- From principles and policies to practice
- Clearer concepts and more evidence
- Children´s agency and data
- Broad stakeholder agency

Set up a core expert group for the project to lead on different aspects of the policy guidance.

Convene regional consultations, including with children, for diverse input into the policy guidance.

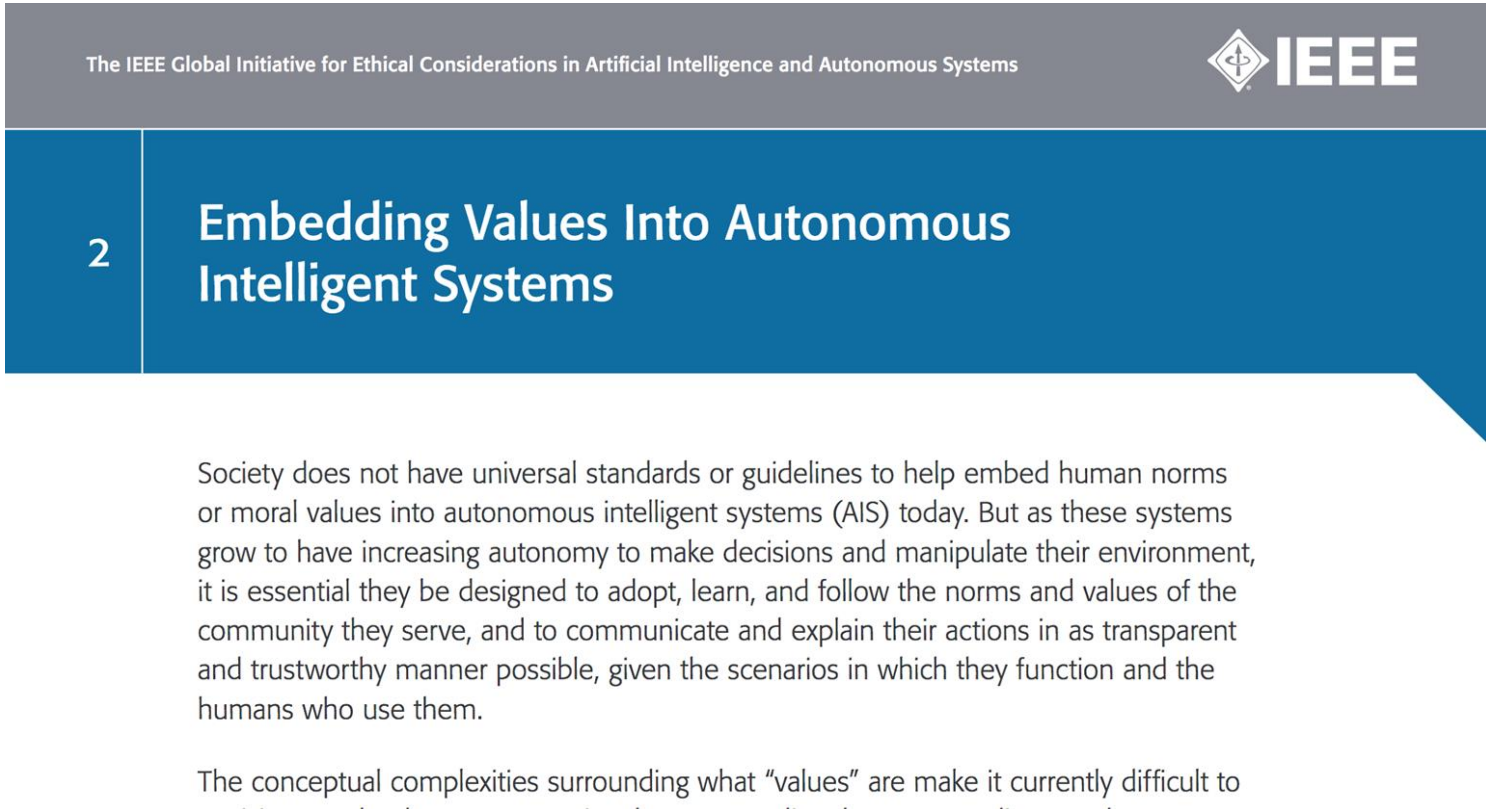
Finalize draft policy guidance.

Co-host AI and Child Rights High-level Forum with Government of Finland in Q2 of 2020, to launch draft guidance.

Identify countries and companies to pilot policy guidance.

UNICEF (2019). AI and Child's Rights Policy. Towards Global Guidance on AI and Child's Rights 26-27 June, 2019, New York, USA, Office of Global Insight and Policy.

Ethical considerations: how



The IEEE Global Initiative for Ethical Considerations in Artificial Intelligence and Autonomous Systems

IEEE

2

Embedding Values Into Autonomous Intelligent Systems

Society does not have universal standards or guidelines to help embed human norms or moral values into autonomous intelligent systems (AIS) today. But as these systems grow to have increasing autonomy to make decisions and manipulate their environment, it is essential they be designed to adopt, learn, and follow the norms and values of the community they serve, and to communicate and explain their actions in as transparent and trustworthy manner possible, given the scenarios in which they function and the humans who use them.

The conceptual complexities surrounding what "values" are make it currently difficult to

D4CR

Ethics by design

Designing for Children's Rights

https://standards.ieee.org/content/dam/ieee-standards/standards/web/documents/other/ead1e_embedding_values.pdf
Charisi, V., Dennis, L., Fisher, M., Lieck, R., Matthias, A., Slavkovik, M., ... & Yampolskiy, R. (2017). Towards moral autonomous systems. arXiv preprint arXiv:1703.04741.

Interdisciplinarity sheet

Disciplines			
Mode of interdisciplinarity	**Integrative synthesis**	**Subordination service**	**Agonistic antagonistic**
Methodological orientations	**Problem-solving**	**Practice-oriented**	**Other**

Interdisciplinarity sheet

Disciplines	• Psychology (social sciences) • Engineering and technology (applied science) • Computer Science, mathematics (formal sciences)		
Mode of interdisciplinarity	**Integrative synthesis**	**Subordination service** Technology as a tool for human-AI interaction	**Agonistic antagonistic** Human-Robot Interaction
Methodological orientations	**Problem-solving**	**Practice-oriented** Design human-robot interactions	**Other**

HUMAINT research topics

1. Decision making
2. Child-robot interaction
3. **AI and EU labour markets**
4. Medicine and healthcare
5. Music

Songül Tolan, Annarosa Pesole, Fernando Martínez-Plumed, Enrique Fernández-Macías, José Hernández-Orallo, Emilia Gómez. Artificial Intelligence and Jobs: From Tasks to Cognitive Abilities. RENIR workshop,Torino, May 2019.

Humans carry out tasks at work

Content	Methods and tools
1. **Physical tasks**	1. **Work organisation**
(a) Strength	(a) Autonomy
(b) Dexterity	(b) Teamwork
2. **Intellectual tasks**	(c) Routine
(a) Information processing:	(I) Repetitiveness
(I) I.P. of uncodified information	(II) Standardization
(II) I.P. of codified information	2. **Technology**
(i) Literacy:	(a) Machines (excluding ICT)
(a) Business	(b) Information and Communication technologies
(b) Technical	(I) Basic ICT
(c) Humanities	(II) Programming
(ii) Numeracy:	
(a) Accounting	
(b) Analytic	
(b) Problem solving:	
(I) Information gathering and evaluation.	
(II) Creativity and resolution.	
3. **Social tasks**	
(a) Serving/attending	
(b) Teaching/training/ coaching	
(c) Selling/influencing	
(d) Managing/ coordinating	

Source: Fernández-Macías and Bisello [2017]

Songül Tolan, Annarosa Pesole, Fernando Martínez-Plumed, Enrique Fernández-Macías, José Hernández-Orallo, Emilia Gómez. Artificial Intelligence and Jobs: From Tasks to Cognitive Abilities. RENIR workshop,Torino, May 2019.

Machine intelligence impact

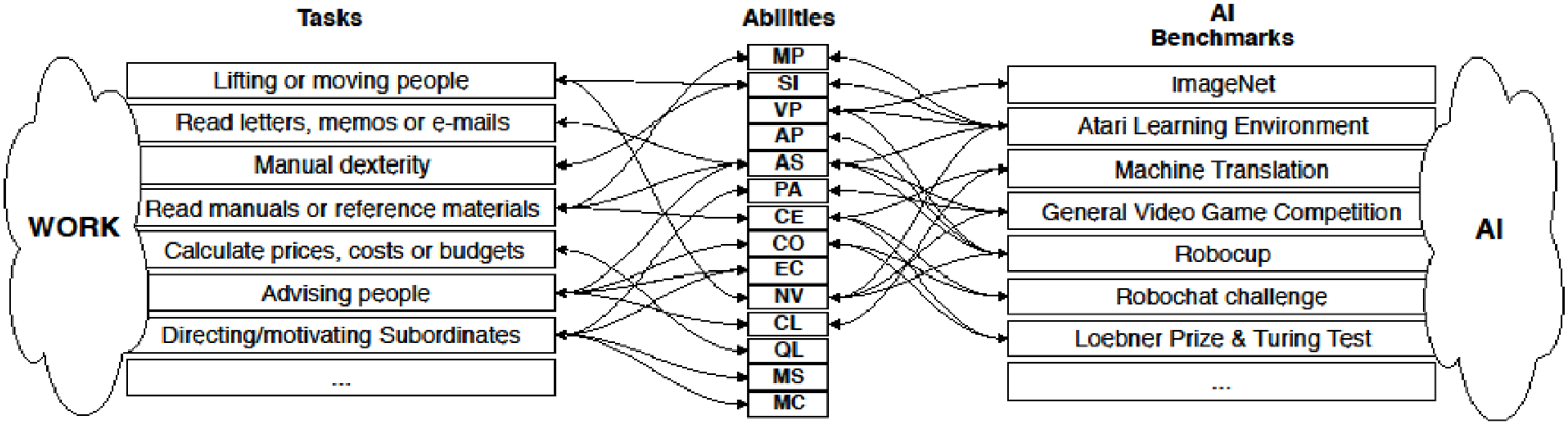
- Technology increases the productivity of all workers, particularly high-skilled workers (Katz and Murphy, 1992)
- Technology also performs labour substitution, polarization
- Approach: task-based framework + work organization (Autor, 2014a,b, Autor et al., 2003; Acemoglu and Autor, 2011)
- We focus on Machine Learning techniques
- We use cognitive abilities as an intermediate step (Hernández-Orallo, 2017)

Cognitive abilities:

- Memory processes
- Sensorimotor interaction
- Visual processing
- Auditory processing
- Attention and search
- Planning and sequential decision making and acting
- Comprehension and compositional expression
- Communication
- Emotion and self-control
- Navigation
- Conceptualisation, learning and abstraction
- Quantitative and logical reasoning
- Mind modeling and social interaction
- Metacognition

Songül Tolan, Annarosa Pesole, Fernando Martínez-Plumed, Enrique Fernández-Macías, José Hernández-Orallo, Emilia Gómez. Artificial Intelligence and Jobs: From Tasks to Cognitive Abilities. RENIR workshop,Torino, May 2019.

From labour to ML paradigms



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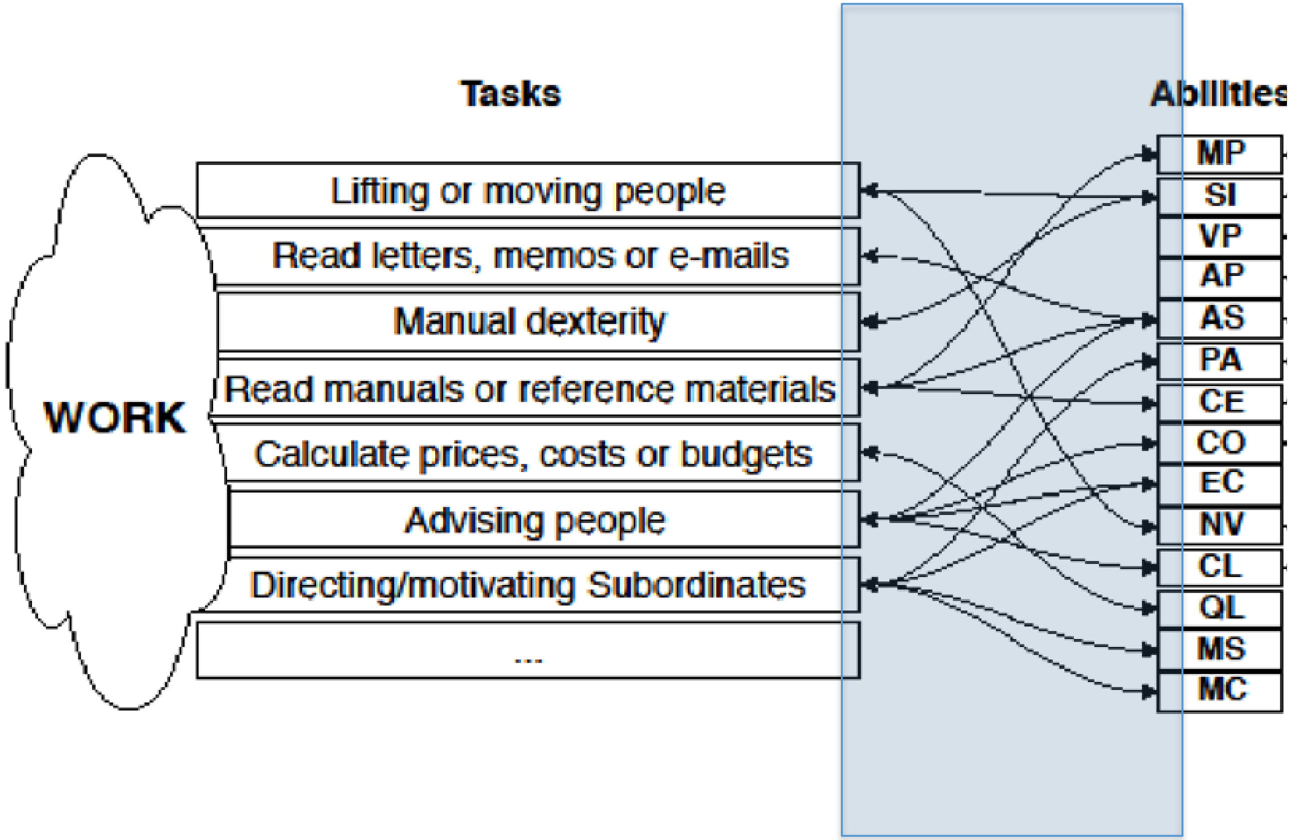
From labour to ML paradigms



- *Delphy* method
- Several rounds of questionnaires to experts
- People do tasks differently than machines
- Discussion and refinement

Table 1: Difference in annotations between round 1 and round 2

	abilities			consensus		
	round 1	round 2	diff.	round 1	round 2	diff.
Average	6.03	5.34	-0.69	65.29%	72.99%	7.70 p.p
Min	0	0	0	28.57%	28.57%	0
Max	13	10	-3	100.00%	100.00%	0

- PCA and clustering of tasks
- Complexity estimation

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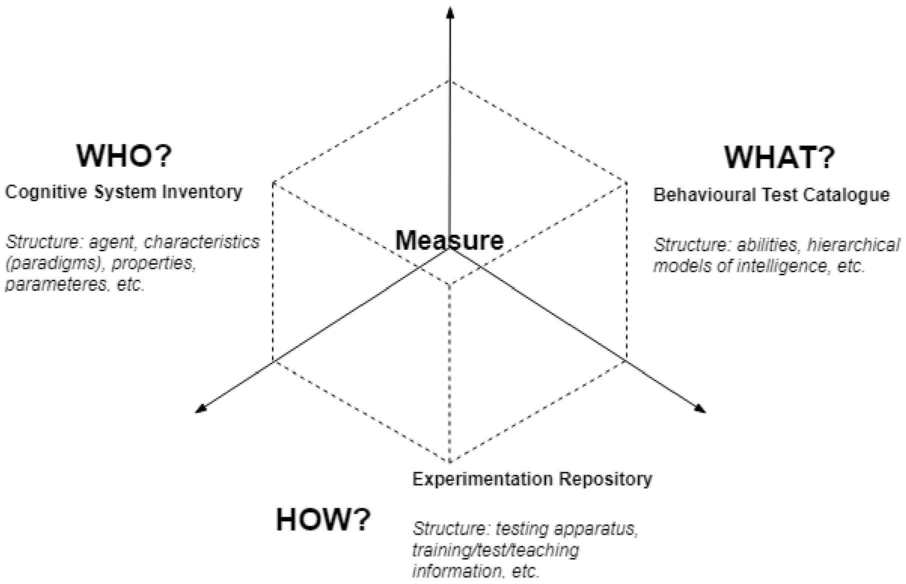
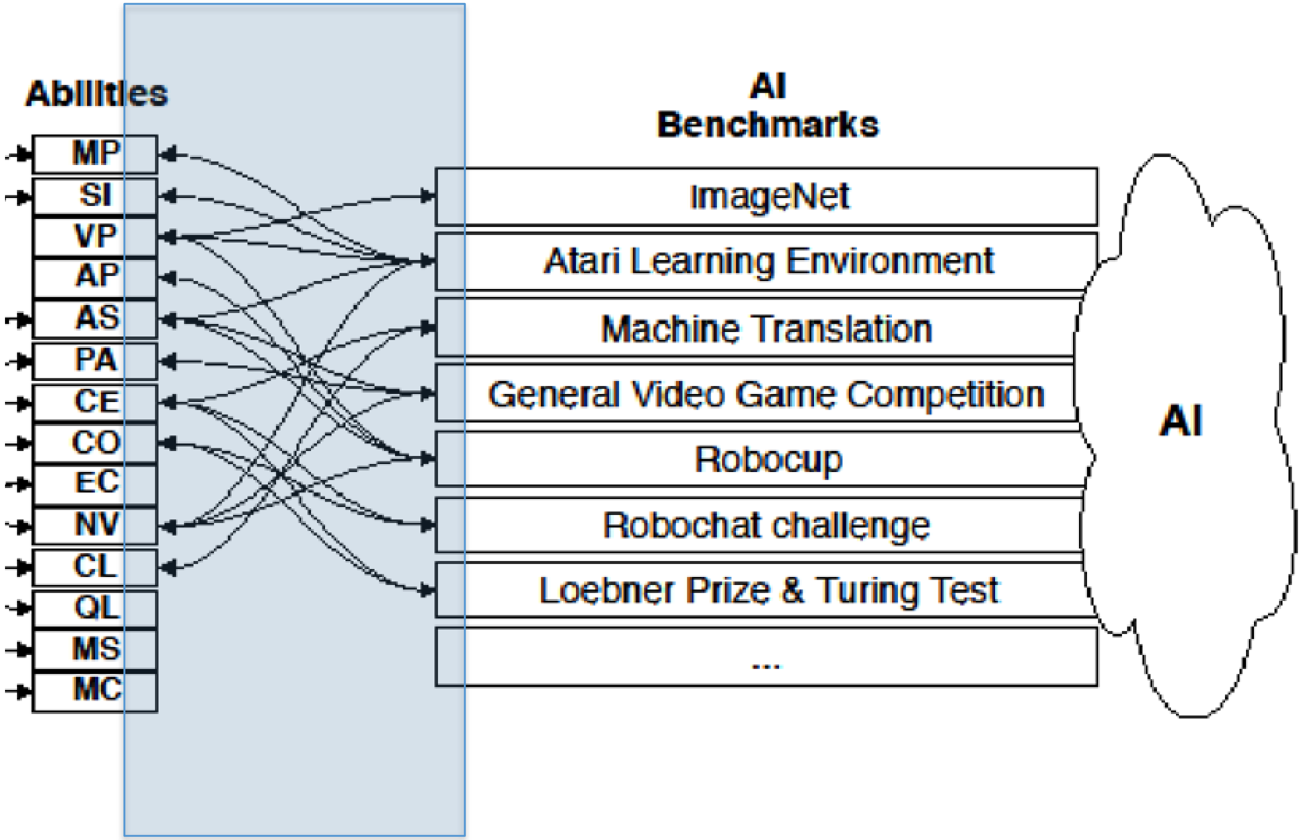
From labour to ML paradigms

https://github.com/nandomp/AICollaboratory

- Analysis, evaluation, comparison and classification of AI systems.
- Data gathered from scientific papers, experiments, benchmarking initiatives.





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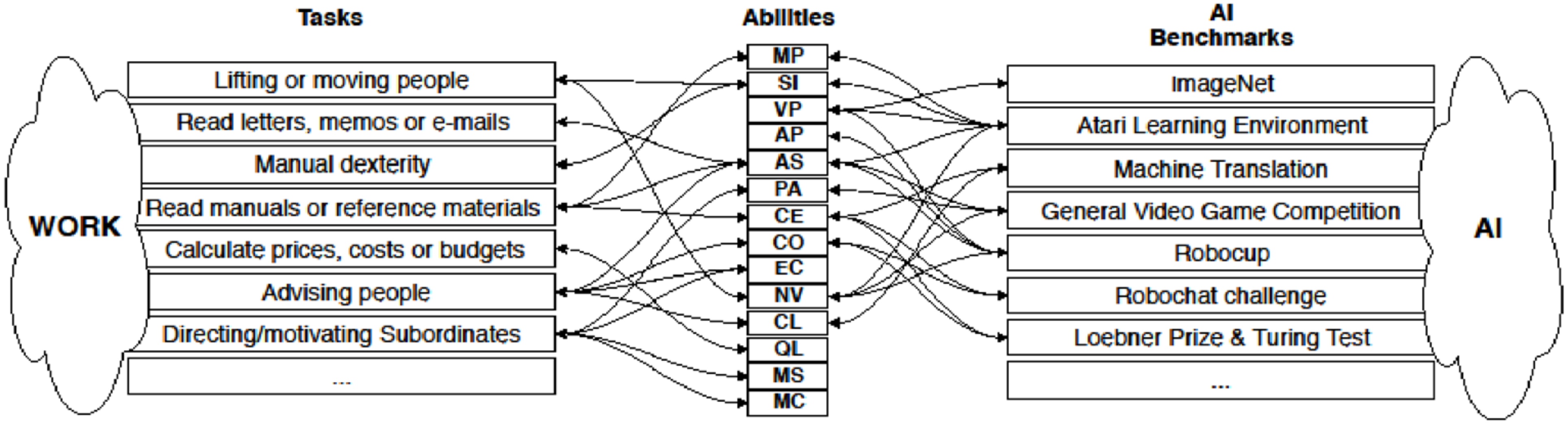
Preliminary conclusions

- ML development has mainly addressed perceptual tasks, e.g. visual and auditory perception
- High percentage of tasks assisted by AI
- AI paradigms towards information processing, memory
- AI benchmarking addressing social skills



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Fernando Martínez-Plumed, Songül Tolan, Jose Hernandez-Orallo, Annarosa Pesole, Enrique Fernández-Macías, Emilia Gómez. Does AI Qualify for the Job? A Bidirectional Model Mapping Labour and AI Intensities, AIES 2020.

Work organization

AAAI / ACM conference on
ARTIFICIAL INTELLIGENCE, ETHICS, AND SOCIETY

- More than a sum of tasks.
- Generality, autonomy, sociability.
- Work organization.
- Digital labour platforms (e.g. Uber, Amazon Mechanical Turk, Task Rabbit): discrete and granular tasks, algorithmically centralised decision making, standardise processes and outputs.

Songül Tolan, Annarosa Pesole, Fernando Martínez-Plumed, Enrique Fernández-Macías, José Hernández-Orallo, Emilia Gómez. Artificial Intelligence and Jobs: From Tasks to Cognitive Abilities. RENIR workshop,Torino, May 2019.
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Interdisciplinarity sheet

Disciplines			
Mode of interdisciplinarity	**Integrative synthesis**	**Subordination service**	**Agonistic antagonistic**
Methodological orientations	**Problem-solving**	**Practice-oriented**	**Other**

Interdisciplinarity sheet

Disciplines	• Economics (social sciences) • Computer Science, mathematics (formal sciences) • Sociology (social sciences) • Psychology (social sciences)		
Mode of interdisciplinarity	**Integrative synthesis** Mathematical model	**Subordination service**	**Agonistic antagonistic**
Methodological orientations	**Problem-solving** Quantification	**Practice-oriented**	**Other**

HUMAINT research topics

1. Decision making
2. Child-robot interaction
3. AI and EU labour markets
4. **Medicine and healthcare**
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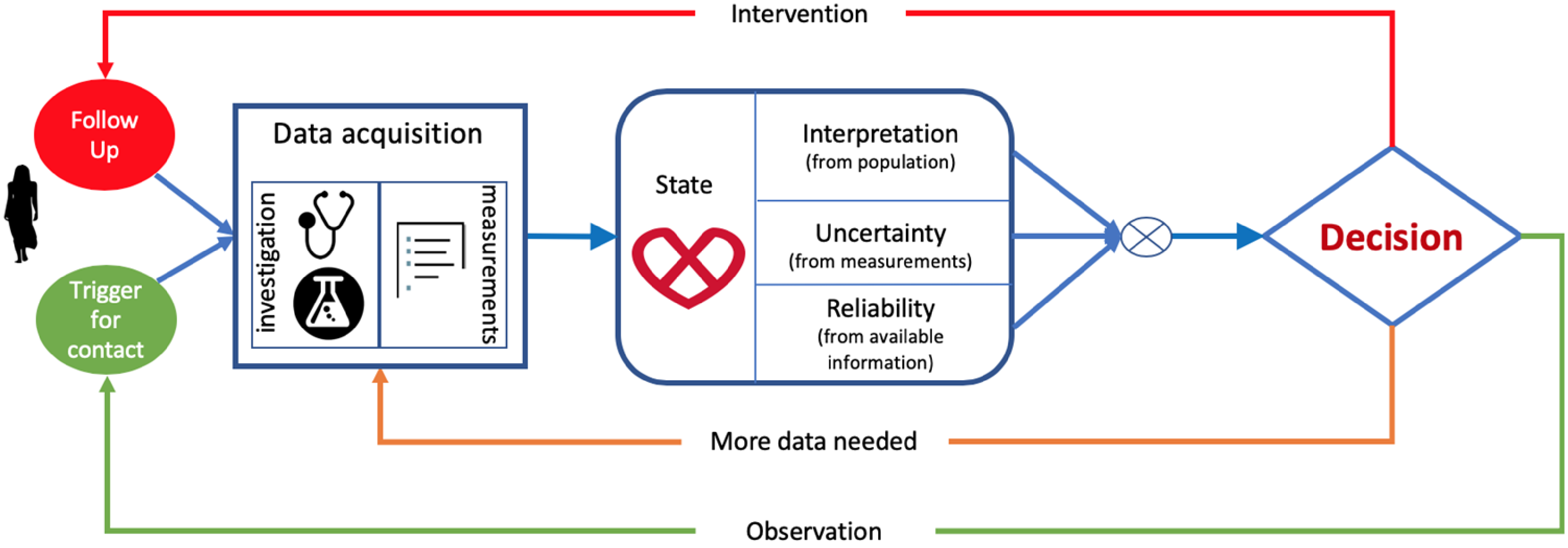
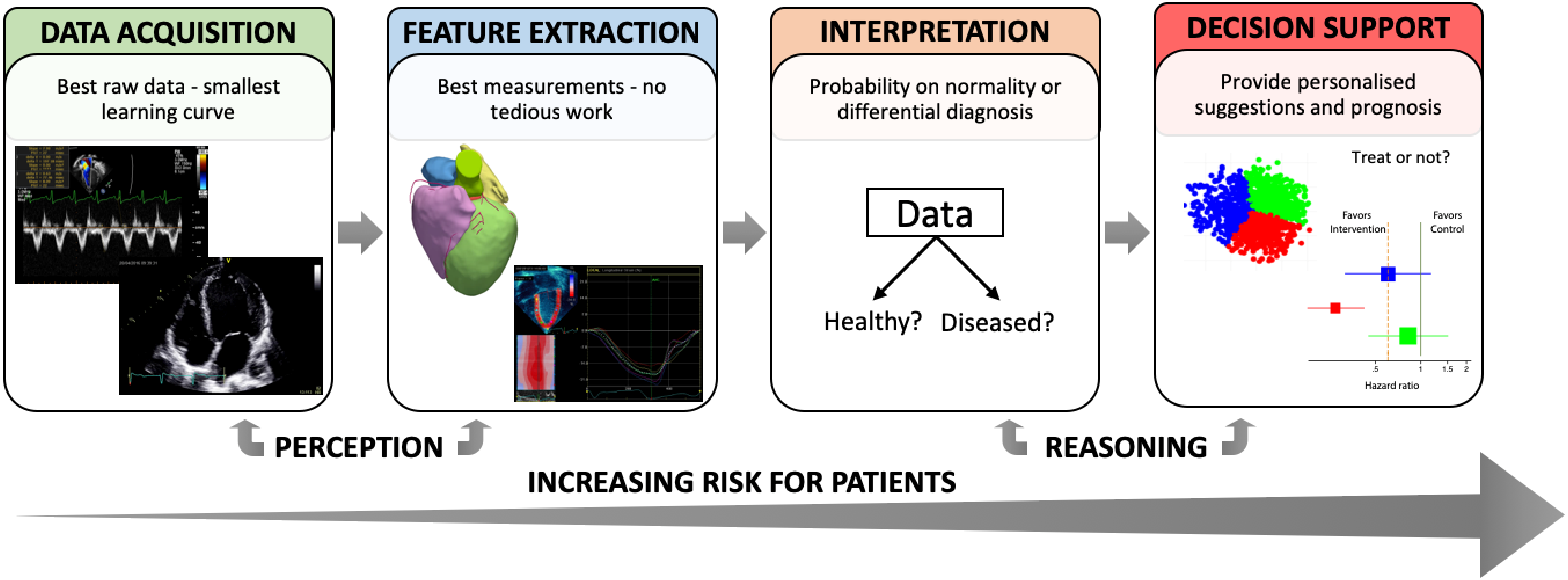
AI in medicine and healthcare

- Clinical decision making



Sanchez-Martinez, S.; Camara, O.; Piella, G.; Cikes, M.; Gonzalez Ballester, M.A.; Miron, M.; Vellido, A.; Gomez, E.; Fraser, A.; Bijnens, B. Machine Learning for Clinical Decision-Making: Challenges and Opportunities. *Preprints* **2019**, 2019110278 (doi: 10.20944/preprints201911.0278.v1).

Machine learning in clinical decision making



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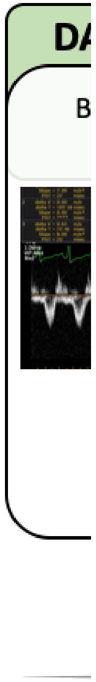
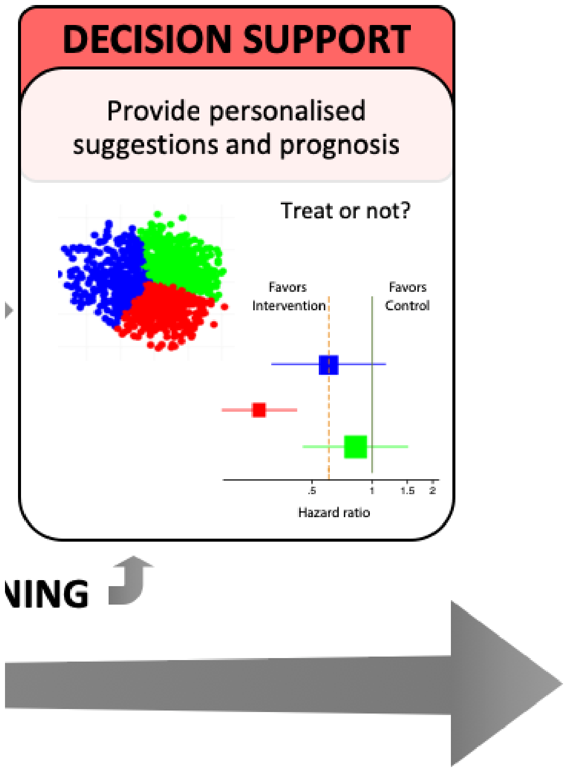


Strengths	Weaknesses
• May enhance the prediction of clinical outcomes • May enhance the prediction of response to treatment • May improve the recommendation of interventions	• Need well-curated, representative databases for training • Affected by data reliability, representativeness, completeness, and bias • Need to prove clinical benefit • Need to be explainable rather than interpretable • Need to be integrated within clinical systems • Need to prove cost-effectiveness
Opportunities	**Threats**
• Lower cost of healthcare by suggesting cost-effective decisions	• Harm patients if wrong decisions are taken – high-risk • Make decisions for the average patient, not at the individual level



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General challenges on ML for clinical decision making

- **Learning**
  - Non-standardized data
  - Bias and confounding
  - Continuous validation
- **Accountability/traceability**
  - Interpretability (slow reasoning) vs explainability (Deep Learning): main limiting factors for adoption.
  - Casual ML rather than predictive ML
- **System-related**
  - Security
  - Regulatory
  - Human-machine interaction
  - Real clinical data

Sanchez-Martinez, S.; Camara, O.; Piella, G.; Cikes, M.; Gonzalez Ballester, M.A.; Miron, M.; Vellido, A.; Gomez, E.; Fraser, A.; Bijnens, B. Machine Learning for Clinical Decision-Making: Challenges and Opportunities. *Preprints* **2019**, 2019110278 (doi: 10.20944/preprints201911.0278.v1).

Beyond clinical decision making

- Literature review of 582 publications, product descriptions, medical perspective
  - Clinical decision-making
    - Radiology, surgery with augmented reality and surgical robots
    - Followed by other image-based specialties (e.g. pathology, dermatology, ophtalmology)
    - Virtually all areas, from from general practitioners to emergency departments, epidemiology, and disease management
  - Online assistants (e-doctors), clinical companions.
  - Wearables and IoT → real-time monitoring
  - Genetic tests in an affordable way

Gómez-González, E., Gómez, E., Márquez-Rivas, J., Guerrero-Claro, M., Fernández-Lizaranzu, I., Relimpio-López, M. I., Dorado, M. E., Mayorga-Buiza, M. J., Izquierdo-Ayuso, G., Capitán-Morales, L. Artificial intelligence in medicine and healthcare: a review and classification of current and near-future applications and their ethical and social Impact, arxiv.

Classification

TAL 0. Unknown status. Not considered feasible according to references.
TAL 1. Unknown status. Considered feasible according to related, indirect references.
TAL 2. General/basic idea publicly proposed.
TAL 3. Calls for public funding of R&D open.
TAL 4. Results of academic/partial projects disclosed.
TAL 5. Early design of product disclosed.
TAL 6. Operational prototype/'first case' disclosed.
TAL 7. Products disclosed but not available.
TAL 8. Available for restricted (e.g. professional) users.
TAL 9. Available for the public.

Gómez-González, E., Gómez, E., Márquez-Rivas, J., Guerrero-Claro, M., Fernández-Lizaranzu, I., Relimpio-López, M. I., Dorado, M. E., Mayorga-Buiza, M. J., Izquierdo-Ayuso, G., Capitán-Morales, L. *Artificial intelligence in medicine and healthcare: a review and classification of current and near-future applications and their ethical and social Impact*, arxiv.

AI and AI-mediated technologies	Specific implementations.	TAL	Social Impact
Algorithms for computer-aided diagnosis.	SW for decision support in (most) clinical areas.	8, 9	Positive
Structured reports, eHealth.	SW for improved workflow, efficiency.	8, 9	
AR/VR, advanced imaging tools.	Tools for information visualization and navigation.	6, 7, 9	
	Image-guided surgery. Teleoperation.	4, 6, 9	
Digital pathology, 'virtopsy'.	SW for automated, extensive analysis.	4-9	
Personalized, precision medicine.	Tailored treatments. Prediction of response.	4-9	
	'In-silico' modeling and testing. The 'digital twin'.	4-8	
	Drug design.	4, 8	
Apps, chatbots, dashboards, online platforms.	The 'digital doctor' (assistance for professionals and for patients).	8, 9	
Companion and social robots.	For hospitalized persons, children & the elderly.	4-9	
Big Data collection and analysis.	Epidemiology, prevention and monitoring of disease outbreaks.	2-9	
	Fraud detection. Quality control, monitoring of physicians and treatments.	4-9	
IoT, wearables, mHealth.	Automated clinical/health surveillance in any environment/institution.	7, 8	
	Monitoring, automated drug delivery.	7-9	
Gene editing.	Disease treatment, prevention.	7, 8	
Merging of medical and social data. 'Social' engineering.	Prevention of episodes with clinical relevance (e.g. suicide attempts).	6, 8	Controversial
	Tailored marketing (e.g. related to female cycles).	6, 8	
Reading and decoding brain signals. Interaction with neural processes.	Treatment of diseases. Restoring damaged functions.	3-8	
	Brain-machine interfaces.	5-8	
	Control of prostheses, exoskeletons. 'Cyborgs'.	2-7	
	Neurostimulation. Neuromodulation.	4-8	
	Neuroprostheses (for the central nervous system).	2-5	
	Mind 'reading' and 'manipulation'.	1-3	
Genetic tests. Population screening.	Disease tests. Direct-to-consumer tests.	4-9	
Personalized, precision medicine.	Individual profiling. Personalized molecules (for treatment) at 'impossible' prices.	3-8	
Gene editing.	'Engineered' humans.	2, 6	
	Gene-enhanced 'superhumans'.	2	
	Self-experimentation medicine. Biohacking.	2, 6	
Fully autonomous AI systems.	The 'digital doctor'.	2-5	
	'Robotic surgeon'.	2, 4	
Human-animal embryos.	Organs for transplants.	2, 4, 5	
	Hybrid beings ('chimera').	2, 4	
The quest for immortality.	Whole-brain emulation / 'transplant'.	1, 2	
The search for artificial life forms.	'Living machines' ('biological robots', 'biobots')	4, 6	
	Military.	2, 3	
Evil biohacking.	Targeting specific individuals or groups.	1, 2	
Weaponization.	From 'small labs' to military labs.	1, 2	
Bioterrorism.	From 'small labs'.	1, 2	Negative

Ethical and social impact

1. Currently under analysis
2. Of particular relevance in this context
3. Barely addressed, specific

Challenges:

- Extended personalized medicine
- Doctor replacement/enhancement → patient-centred view
- Affordability / inequalities
- **Dual use of technology**

Gómez-González, E., Gómez, E., Márquez-Rivas, J., Guerrero-Claro, M., Fernández-Lizaranzu, I., Relimpio-López, M. I., Dorado, M. E., Mayorga-Buiza, M. J., Izquierdo-Ayuso, G., Capitán-Morales, L. *Artificial intelligence in medicine and healthcare: a review and classification of current and near-future applications and their ethical and social Impact*, arxiv.

(G1) Currently under analysis, as raised by other areas of AI applications.

Aspects.	Questions.
Data privacy, integrity.	Ownership. Authorization for data collection, sharing, mining, exchange.
Anonymity.	Surveillance anxiety.
Responsibility. Accountability.	Who is responsible in case of malfunction?
Effects on professionals and employment.	Lost & new jobs. Deep changes in some medical specialties (some may even disappear). Need of professional updating. Quality control, monitoring.
Security. Reliability.	Vulnerabilities. Data theft. Manipulation of the data used to train the systems.
Performance.	Improved health outcomes and clinical pathways. Reduction of medical errors. 'Personalized Medicine'. Psycho-social outcomes.
Human-in-the-loop?	Should a human operator override AI systems? Even if human is more 'error-prone'? What happens if there is no time to act?

Aspects.	Controversies.	
Explainability.	Currently required by legislation. Some systems are (will be) too complex to be understood by a human. But they may give better results than a human.	(G2) Of particular relevance for AI applications in Medicine and Health Care.
Trust.	Does 'the machine' perform better than a human doctor? What to do if they (AI system, human doctor) give conflicting opinions? 'Digital health scammers'.	
Data quality. Bias / fairness.	Do AI systems have biases/are fair with different (e.g. ethnic, gender, age) groups? Do they receive proper, balanced data for training? Are results valid?	
Empathy.	Shared decisions? Help (the human) take difficult decisions?	
Citizen (taxpayer) opinion and involvement.	Common-good in public-funded research, informed consent, citizen science. Reduced 'asymmetry' doctor-patient. 'Patient-centric' model.	
Test, benchmarking.	How to evaluate results? Existing procedures for average groups are valid for individualized treatments? Comparison of AI systems 'against humans or machines'?	
Regulation.	Lags behind technology. No international consensus.	
Affordability. Economic impact.	Optimal treatments at 'impossible' prices? A factor of inequality? New models for health insurance and coverage?	
Information for the public and professionals.	Pressure for new products. Real advances vs hypes and non-confirmed stories of success in areas of great interest (e.g. cancer cures). Risk of 'fake-based' medicine.	
Life and death decisions.	Should we allow 'a machine' to take them (on us, on a relative)? The debate about lethal autonomous weapon systems.	

Aspects.	Significant/conflicting issues.	
Humanization of care.	Professionals with AI: More time with the patient, stress relief. AI systems: Currently, lack of physical exam/contact with patient.	(G3) Barely/not included in analysis of AI applications in Medicine and Heath Care.
Social engineering, profiling based on merged medical, health, social data.	Preventive detection of events (e.g. suicide) vs tailored marketing, insurance, health care, employment. Genetic screening of the population.	
Availability of (unsupervised, unreliable) multiple data, genetic tests for anyone.	Risk of 'patient-generated' medicine.	
Limits to data use? Post-mortem, inheritance.	Post-mortem use of individual (e.g. genetic) information?	
Crowd-sourcing of algorithms, processing power.	Free sharing of expertise, know-how, experience. Solidarity vs risks of malicious use.	
Reading, decoding brain signals.	Hope for severely impaired vs privacy at its basics.	
Interaction with neural processes.	Help for neurological, mental diseases vs free will.	
Gene editing as self-experimentation.	Risk of unexpected results. Change of genetic heritage.	
Gene editing of (human, human-animal) embryos.	Risk of unexpected results in newborns. Creation of new beings ('chimera').	
The two sides of technology.	'Easy' weaponization. High risk for bioterrorism.	
Whole-brain emulation / 'transplant'.	The quest for immortality. Definition of life.	
'Living machines' ('biological robots', 'biobots') The search for artificial life forms.	Definitions of life (natural, artificial) and death.	
Benefits versus risks and pitfalls.	**Limits (or no) to research and development?**	

Interdisciplinarity sheet

Disciplines			
Mode of interdisciplinarity	**Integrative synthesis**	**Subordination service**	**Agonistic antagonistic**
Methodological orientations	**Problem-solving**	**Practice-oriented**	**Other**

Interdisciplinarity sheet

Disciplines	• Engineering and Technology (applied sciences) • Medicine and health (applied sciences)		
Mode of interdisciplinarity	**Integrative synthesis**	**Subordination service**	**Agonistic antagonistic**
Methodological orientations	**Problem-solving**	**Practice-oriented**	**Other**

HUMAINT research topics

1. Decision making
2. Child-robot interaction
3. AI and EU labour markets
4. **AI and music**

TROMPA Human-centred Music Information Retrieval Technologies

AI also impacts music

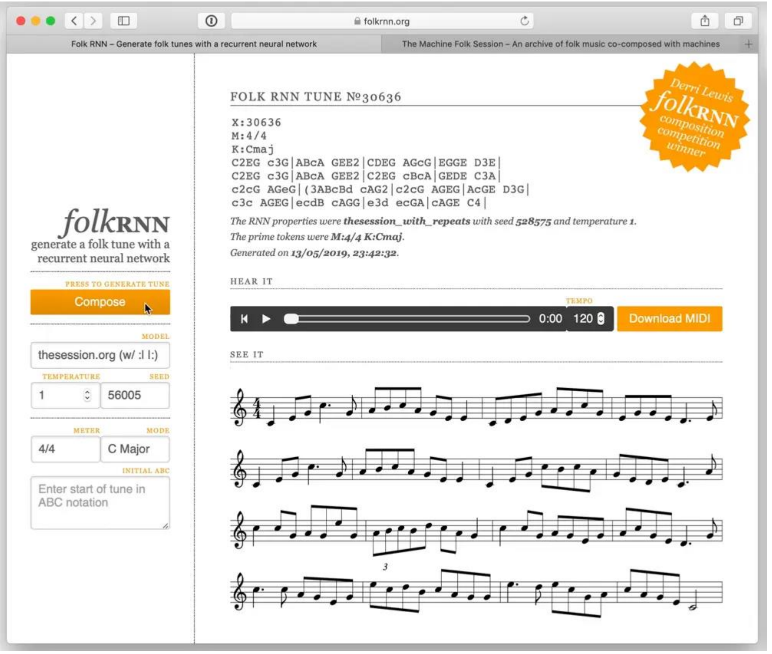
- Exploited in all stages, from creation to distribution (platforms)
- Various participants contributing to and benefiting from music: composers, musicians, educators, listeners, and organisations.
- Focus on 2 contexts
    a. AI for music creation: realistic synthesis/composition
    b. AI for music recommendation

Taryn Southern 2017

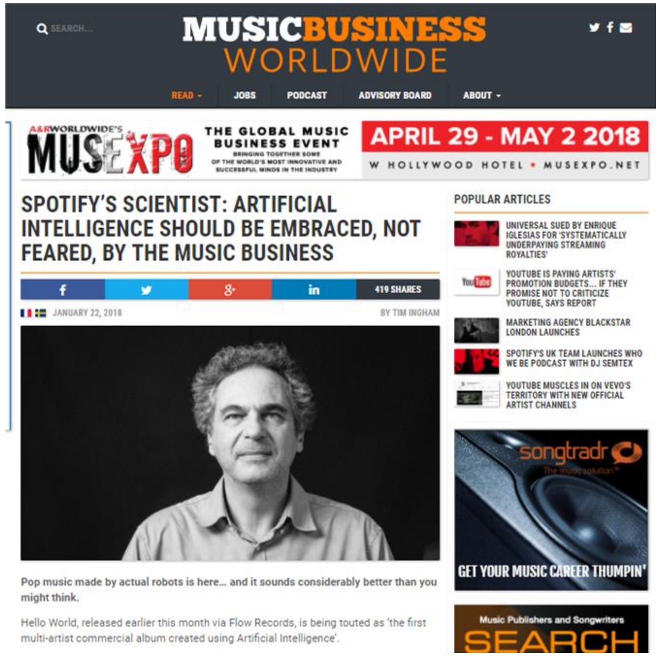
Deep bach https://www.youtube.com/watch?v=QiBM7-5hA6o

Impact of AI on music creativity

- Collaboration with Bob Sturm (Computer science), María Iglesias (Law). Oded Ben-Tal (Music composer).
- Copyright law & Engineering practice
- Around folk-NN project https://folkrnn.org/ generate a folk tune with a recurrent neural network. https://www.youtube.com/watch?v=EC1TrQzBVSE



European Research Council



Bob L.T. Sturm, Maria Iglesias, Oded Ben-Tal, Marius Miron and Emilia Gómez. Artificial Intelligence and Music: Open Questions of Copyright Law and Engineering Praxis. Arts 2019, 8(3)

AI for music creativity: questions

1. In many areas technology leads to more efficient production lines and increased profit but human redundancy and deskilling. Can the same happen in music?
2. Who (and how) is accountable for music-AI systems?
3. Who owns the rights to the music generated by AI models? What is their artistic value?
4. Should musicians be informed about the involvement of AI in the music they play, much the same way ingredients of food products are communicated? What about composers using AI tools?
5. How should this information be presented in a transparent way, and to what level of detail?

Bob L.T. Sturm, Maria Iglesias, Oded Ben-Tal, Marius Miron and Emilia Gómez. Artificial Intelligence and Music: Open Questions of Copyright Law and Engineering Praxis. Arts 2019, 8(3)

Some findings

Copyright Law perspective

- Authorship recognition & copyright may require an analysis of the operation of the systems and the role of the different actors involved (e.g. developer, trainer, user) → transparency/accountability.

Engineering perspective

- Started discussions on FAT-MIR

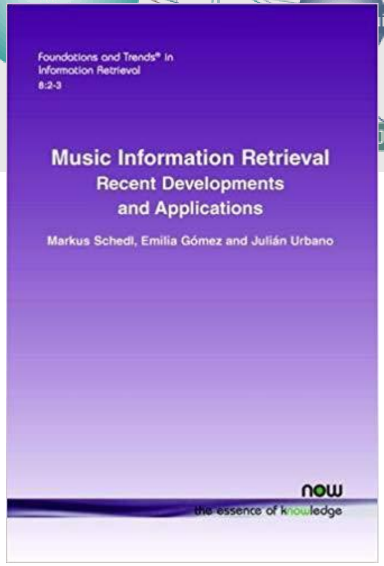
ISMIR 2019:
20th Conference of the International Society for Music Information Retrieval

Bob L.T. Sturm, Maria Iglesias, Oded Ben-Tal, Marius Miron and Emilia Gómez. Artificial Intelligence and Music: Open Questions of Copyright Law and Engineering Praxis. Arts 2019, 8(3)

Gomez, E., Holzapfel, A., Miron, M., Sturm, B. L. Fairness, Accountability and Transparency in Music Information Research (FAT-MIR), ISMIR tutorial, 2019 https://zenodo.org/record/3546227#.XiQe6lNKgUE

Music recommender systems

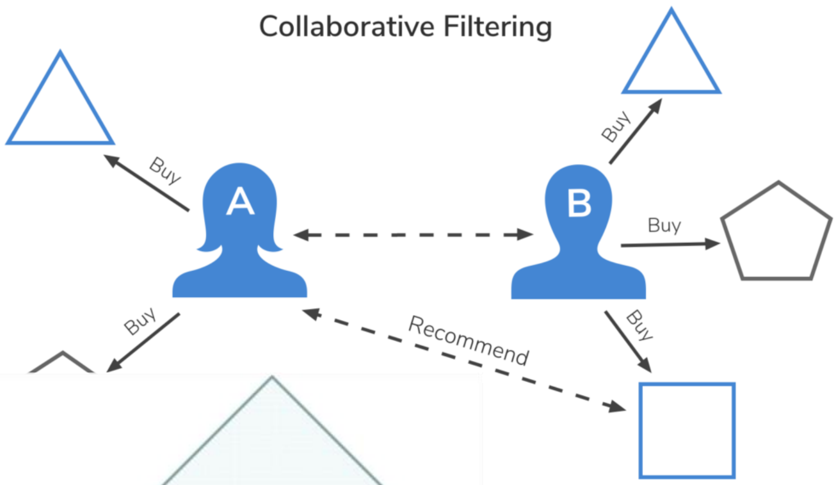
- Based on the concept of similarity
  - User similarity
  - Artist similarity
  - Music content similarity
- Approaches

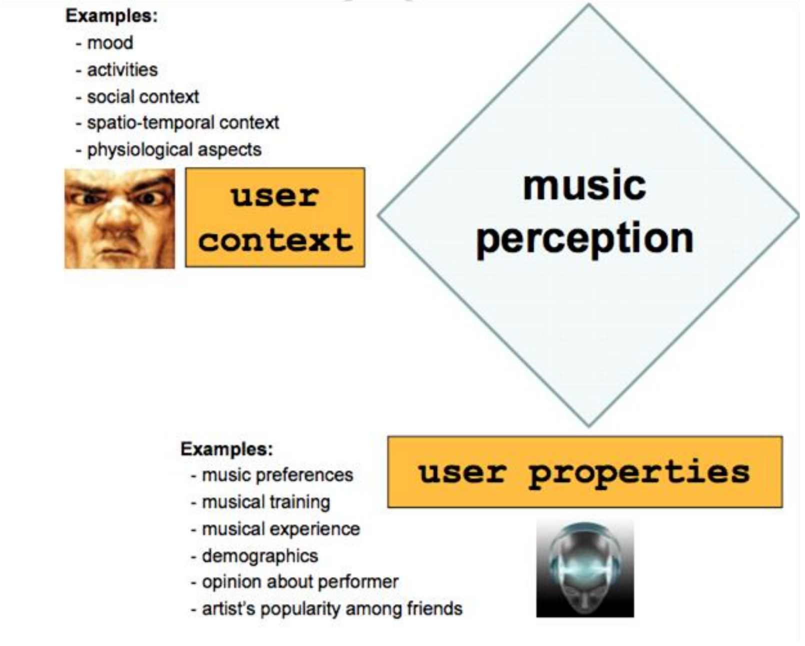


M. Schedl, E. Gómez, and J. Urbano, "Music Information Retrieval: Recent Developments and Applications," Foundations and Trends® in Information Retrieval, vol. 8, no. 2–3, pp. 127-261, Sep. 2014. doi: 10.1561/1500000042

Music recommender systems

- Based on the concept of similarity
  - User similarity
  - Artist similarity
  - Music content similarity
- Approaches
  - Collaborative filtering: similar listeners

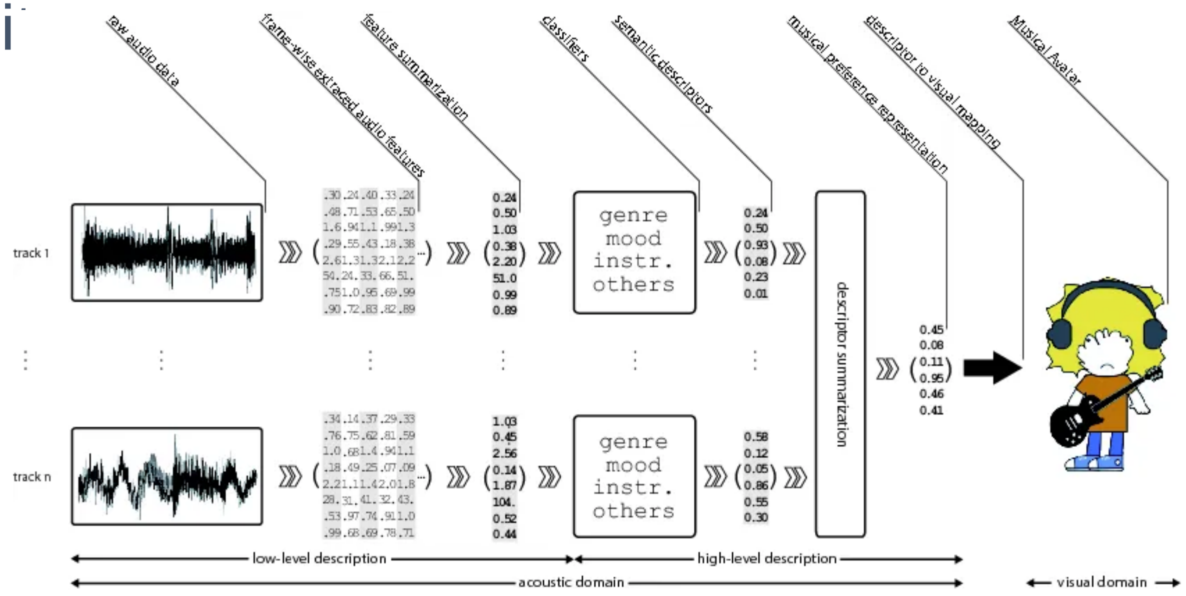




M. Schedl, E. Gómez, and J. Urbano, "Music Information Retrieval: Recent Developments and Applications," Foundations and Trends® in Information Retrieval, vol. 8, no. 2–3, pp. 127-261, Sep. 2014. doi: 10.1561/1500000042

Music recommender systems

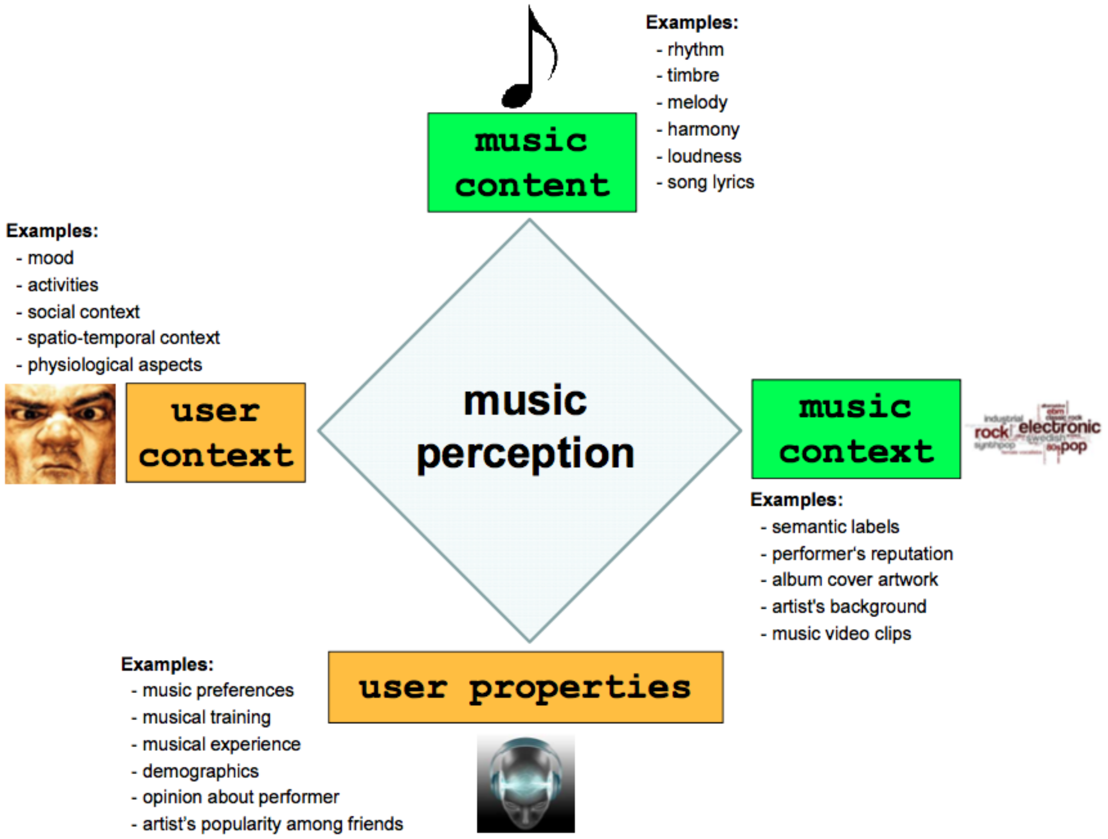
- Based on the concept of similari
  - User similarity
  - Artist similarity
  - Music content similarity
- Approaches
  - Collaborative filtering
  - Music content description



M. Schedl, E. Gómez, and J. Urbano, "Music Information Retrieval: Recent Developments and Applications," Foundations and Trends® in Information Retrieval, vol. 8, no. 2–3, pp. 127-261, Sep. 2014. doi: 10.1561/1500000042

Music recommender systems

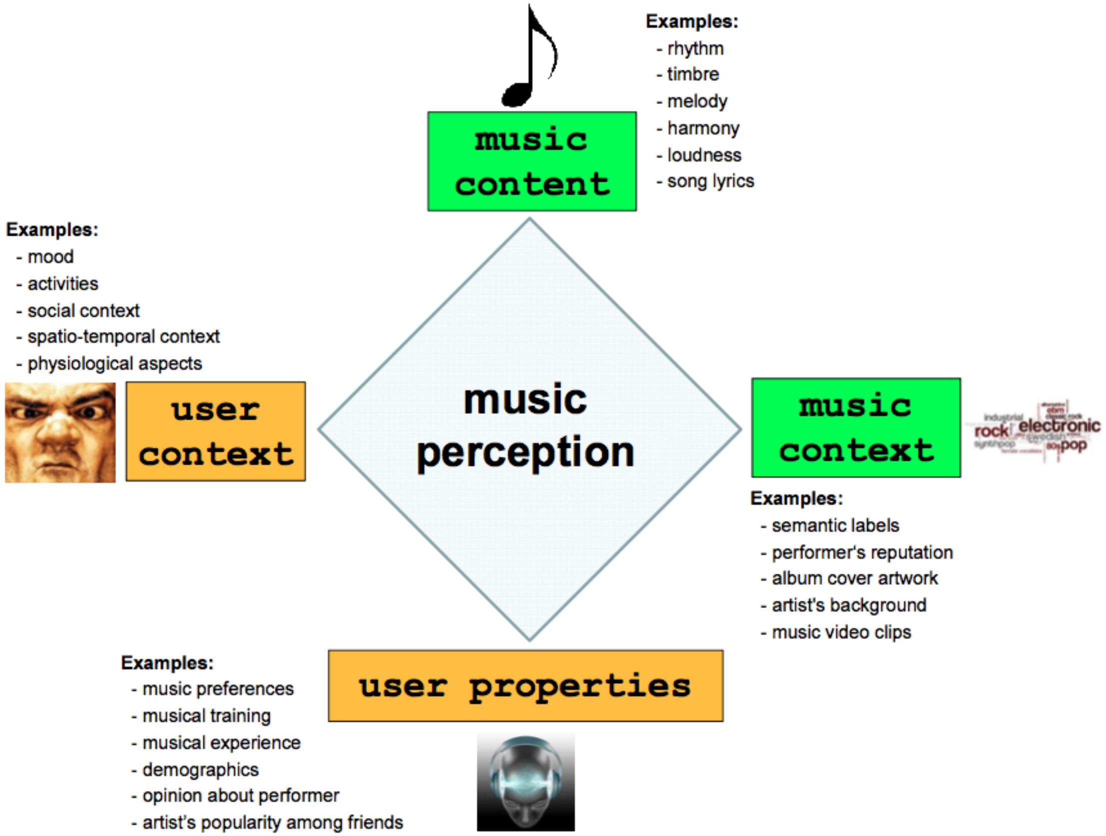
- Based on the concept of similarity
  - User similarity
  - Artist similarity
  - Music content similarity
- Approaches
  - Collaborative filtering
  - Music content description
  - Music context description (web, lyrics, editorial metadata)



M. Schedl, E. Gómez, and J. Urbano, "Music Information Retrieval: Recent Developments and Applications," Foundations and Trends® in Information Retrieval, vol. 8, no. 2–3, pp. 127-261, Sep. 2014. doi: 10.1561/1500000042

Music recommender systems

- Based on the concept of similarity
  - User similarity
  - Artist similarity
  - Music content similarity
- Approaches
  - Collaborative filtering
  - Music content description
  - Music context description
  - Hybrid
- Similarity vs diversity dilemma



M. Schedl, E. Gómez, and J. Urbano, "Music Information Retrieval: Recent Developments and Applications," Foundations and Trends® in Information Retrieval, vol. 8, no. 2–3, pp. 127-261, Sep. 2014. doi: 10.1561/1500000042

Designing music recommenders

** Images from: https://search.creativecommons.org/

Benjamin, W. *The Work of Art in the Age of Mechanical Reproduction* (Hannah Arendt, ed., Illuminations. London: Fontana, 1968 (1935)).

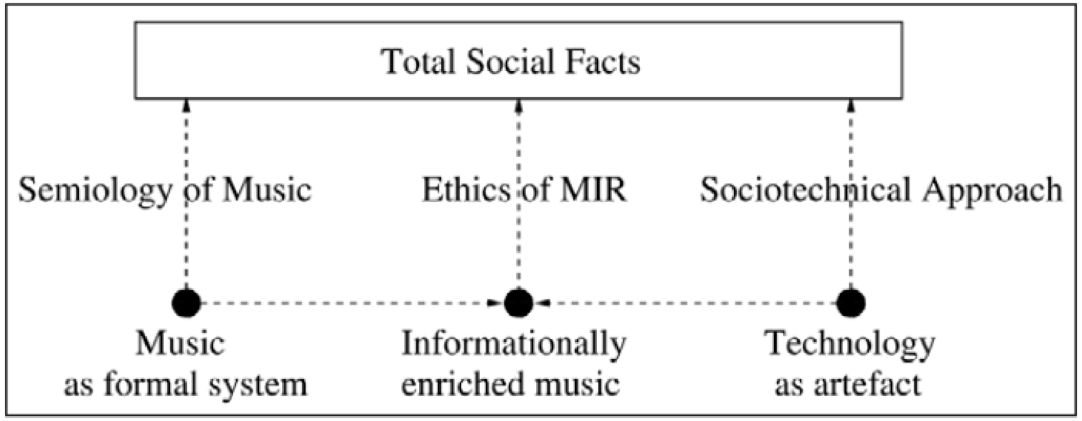
THE ABSTRACTION TRAPS IN DESIGNING SOCIOTECHNICAL SYSTEMS

1. *The Framing Trap*: Failure to model the entire system over which a social criterion will be enforced.
2. *The Portability Trap*: Failure to understand how repurposing algorithmic solutions designed for one social context may be misleading, inaccurate, or otherwise do harm when applied to a different context.
3. *The Formalism Trap*: Failure to account for the full meaning of social concepts which can be procedural, contextual, and contestable, and cannot be resolved through mathematical formalisms.
4. **The Ripple Effect Trap**: Failure to understand how the insertion of technology into an existing social system changes the behaviors and embedded values of the pre-existing system.
5. *The Solutionism Trap*: Failure to recognize the possibility that the best solution to a problem may not involve technology.

Selbst, A. D., Boyd, D., Friedler, S. A., Venkatasubramanian, S. & Vertesi, J. *Fairness and Abstraction in Sociotechnical Systems*. In ACM Conference on Fairness, Accountability, and Transparency (FAT*), vol. 1, 59–68 (2018).

Changes in music listening

Music technologies are not neutral, they influence human perception and cognitive processes.



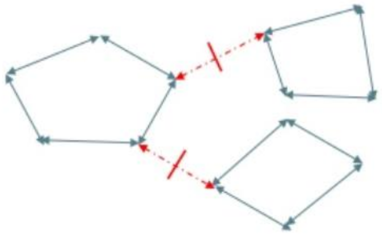
Holzapfel, A., Sturm, B. L. & Coeckelbergh, M. *Ethical Dimensions of Music Information Retrieval Technology*. Transactions of the International Society for Music Information Retrieval 1, 44–55 (2018).

“We should be concerned about the loss of cultural diversity for the same reason that biologists worry about the loss of biodiversity: we don’t yet know what the loss will mean, but we do know that the loss will be irreversible.”

Huron, D. *Issues and Prospects in Studying Cognitive Cultural Diversity*. In Proceedings of the 8th International Conference on Music Perception & Cognition, August (2004).

Phenomena linked to similarity, lack of diversity

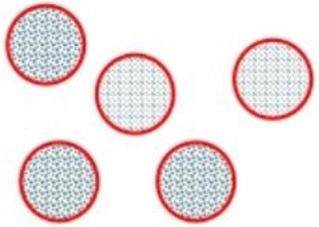
Filter Bubbles



Over-exposition to content which fits personal interests, hiding the diverse from the online experiences.

Parisier, E. *The filter bubble: What the Internet is hiding from you* (Penguin Press, New York, 2011).

Echo Chambers



Tendency to relate mainly with like-minded people in online spaces, reinforcing polarization.

Sunstein, C. *Echo Chambers: Bush v. Gore Impeachment, and Beyond* (Princeton University Press, 2001).

Cyberbalkanization

Appearance of online communities where frontiers shift from being geographical to being interests-based.

Van Alstyne, M. & Brynjolfsson, E. *Global Village or Cyber-Balkans? Modeling and Measuring the Integration of Electronic Communities*. Management Science 51, 851–868 (2005).

Goals (PhD thesis by Lorenzo Porcaro)

Develop a Framework for Defining and Evaluating Music Recommendation Diversity

Assess Music Recommendation Diversity

Understand the Consequences of Music Recommendation Diversity

Propose Countermeasures for Tuning Music Recommendation Diversity

https://lorenzoporcaro.wordpress.com/

Diversity of music recommender systems

The Specialties of Music Recommendation

very low consumption time in the dimension of minutes, whereas a book or a travel are consumed during days or weeks;

consumption in sequences (e.g., playlists);

music often consumed passively (e.g., while jogging, travelling, working);

consumption is highly driven by situational context;

users are likely to appreciate the re-recommendation of the same item while a user is less likely to read the same news article over and over again;

music evokes strong emotions.

Bauer, C. *The potential of the confluence of theoretical and algorithmic modeling in music recommendation*. In Proceedings of the ACM CHI 2019 Workshop on Computational Modeling in Human-Computer Interaction, May (2019).

Future Directions and Visions in Music Recommender Systems Research

Psychologically-inspired music recommendation

Situation-aware music recommendation

Culture-aware music recommendation

Schedl, M., Zamani, H., Chen, C.-W., Deldjoo, Y. & Elahi, M. *Current Challenges and Visions in Music Recommender Systems Research*. International Journal of Multimedia Information Retrieval 7, 95–116 (2018).

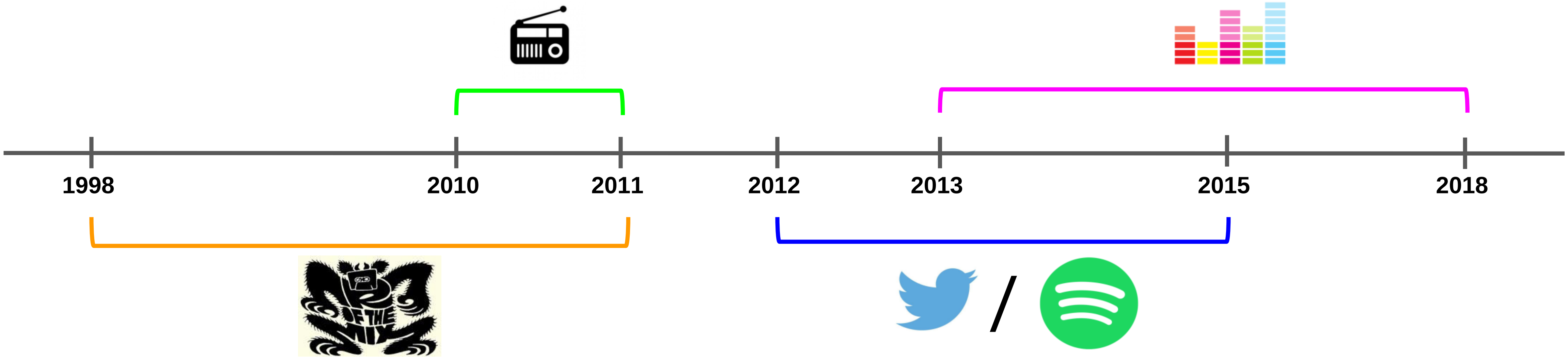
Preliminary outcomes

Lorenzo Porcaro, Emilia Gómez (2019). *20 Years of Playlists: A Statistical Analysis on Popularity and Diversity*. 20th Conference of the International Society for Music Information Retrieval (ISMIR 2019), TU Delft, Delft, 4th-8th November.

Exploration of standard diversity measures from the Information Theory literature for performing comparative analysis of playlist datasets.

- Quantitative Approach
- Comparative Analysis (Historical/Technological)
- Playlist as a Static Object
- Information Theory / Information Retrieval background

** https://github.com/MTG/playlists-stat-analysis



AOTM[1]
 # tracks: 972K
 # playlist: 100K
type: user-generated
catalogue: user

CORN[2]
 # tracks: 15K
 # playlist: 75
type: radio playlist
catalogue: radio

SPOT[3]
 # tracks: 2M
 # playlist: 175
type: user-generated
catalogue: streaming

DEEZ[4]
 # tracks: 227K
 # playlist: 82K
type: user-generated
catalogue: streaming

[1] McFee, B., & Lanckriet, G. “*Hypergraph models of playlist dialects*”. Proceedings of the 13th International Society for Music Information Retrieval Conference 343–348. 2012
[2] S. Chen, J.L. Moore, D. Turnbull, and T. Joachims. “*Playlist prediction via metric embedding*”, Proc. of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD ’12, 2012
[3] M. Pichl, E. Zangerle, and G.Specht. “*Towards a Context-Aware Music Recommendation Approach: What is Hidden in the Playlist Name?*”, Proc. of the 15th IEEE International Conference on Data Mining Workshop , pp. 360–1365, 2016
[4] Crawled in-house

Dataset Characterization

#1 - Popularity

a. Track popularity as track frequency in the dataset

b. Playlist popularity as average track popularity

Simpson and Shannon indexes → measure of evenness between tracks popularity

Gini coefficient → balance between playlists popularity

#2 - Semantic Diversity

a. Semantic information from tag-embeddings

b. Semantic distance between tracks as weighted sum of tag-distance

c. Playlist diversity as average of tracks' pairwise tag-distance

Descriptive statistics → playlist diversity trends

Gini coefficient → balance between playlists diversity

Preliminary conclusions

- ➔ Proposed metrics reflects differences between playlist datasets
  - ◆ Streaming user-generated playlist datasets present a shorter long tail
  - ◆ Radio playlists more (tag)diverse than user-generated playlists
- ➔ Datasets biased towards Western culture (i.e. need for more non-Western playlist datasets!)
- ➔ Software for playlist dataset analysis publicly available https://github.com/MTG/playlists-stat-analysis

Preliminary outcomes (ii)

Lorenzo Porcaro, Emilia Gómez (2019). *A Model for Evaluating Popularity and Semantic Information Variations in Radio Listening Sessions.* 1st Workshop on the Impact of Recommender Systems (ImpactRS), co-located at the 13th ACM Conference on Recommender Systems (RecSys 2019), Copenaghen, 16th-20th September.

First attempt of proposing new measures for evaluating the variations of recommendation lists in different listening scenarios.

- Qualitative Approach
- Mathematical Modelling of Variations
- Playlist as a Dynamic Object
- Set Theory / Calculus background

Table 1: Seed tracks and related features

track ID	Title	Artist	Year	Popularity	Tags
A	Strange Way	Firefall	1979	0.42	album rock, classic rock, country rock
B	My Sharona	The Knack	1979	0.68	album rock, power pop
C	Sugar Walls	Sheena Easton	1985	0.45	mellow gold, minneapolis
D	Like A Virgin	Madonna	1985	0.76	dance pop
E	We Got A Love Thang	CeCe Peniston	1992	0.41	diva house, hip house, vocal house
F	Under The Bridge	Red Hot Chili Peppers	1992	0.83	alternative rock, funk metal, funk rock
G	Sick of Being Lonely	Field Mob	2003	0.44	atl hip hop, dirty south rap, gangster rap
H	In Da Club	50 Cent	2003	0.77	east coast hip hop, gangster rap, hip hop
I	Stay The Night	Zedd feat. Hayley Williams	2014	0.73	complextro, dance pop, edm
J	Happy	Pharrell Williams	2014	0.80	pop, pop rap

Interdisciplinarity sheet

Disciplines			
Mode of interdisciplinarity	**Integrative synthesis**	**Subordination service**	**Agonistic antagonistic**
Methodological orientations	**Problem-solving**	**Practice-oriented**	**Other**

Interdisciplinarity sheet

Disciplines	• Engineering and Technology (applied sciences) • Music (humanities) • Law (humanities) • Sociology (social sciences) • Psychology (social sciences)		
Mode of interdisciplinarity	**Integrative synthesis**	**Subordination service**	**Agonistic antagonistic** FAT-MIR
Methodological orientations	**Problem-solving**	**Practice-oriented**	**Other**

Assessing the impact of AI on human behaviour: interdisciplinary views

Emilia Gómez

@emiliagogu

Joint work/slides from Vicky Charisi, Marius Miron, Songül Tolan, Nando Martínez-Plumed, Enrique Fernández-Macías, Annarosa Pesole, Maria Iglesias (JRC); Carlos Castillo, Lorenzo Porcaro (UPF); José H. Orallo (UPV); Luis Merino, Fernando Caballero (UPO); Bob Sturm (KTH); Emilio Gómez-González (US)

European Commission

Joint Research Centre