

ENHANCING ACCELERATORS MODELING, CONTROL AND ASSOCIATED TECHNOLOGY WITH AI APPLICATION

BARBARA DALENA CEA Paris-Saclay and Paris-Saclay University

ADNAN GHRIBI CNRS Ganil & CEA Paris-Saclay

ACKNOWLEDGEMENTS AND REMARKS

For give me the possibility to review the AI for the Accelerators Bureau de la Division Accélérateurs de la Société Française de Physique

For useful discussions and for providing material F. Gargiulo, F. Poirier, V. Gautard, S. Liuzzo, S. Marini, F. Massimo, I. Andriyash, D. Uriot

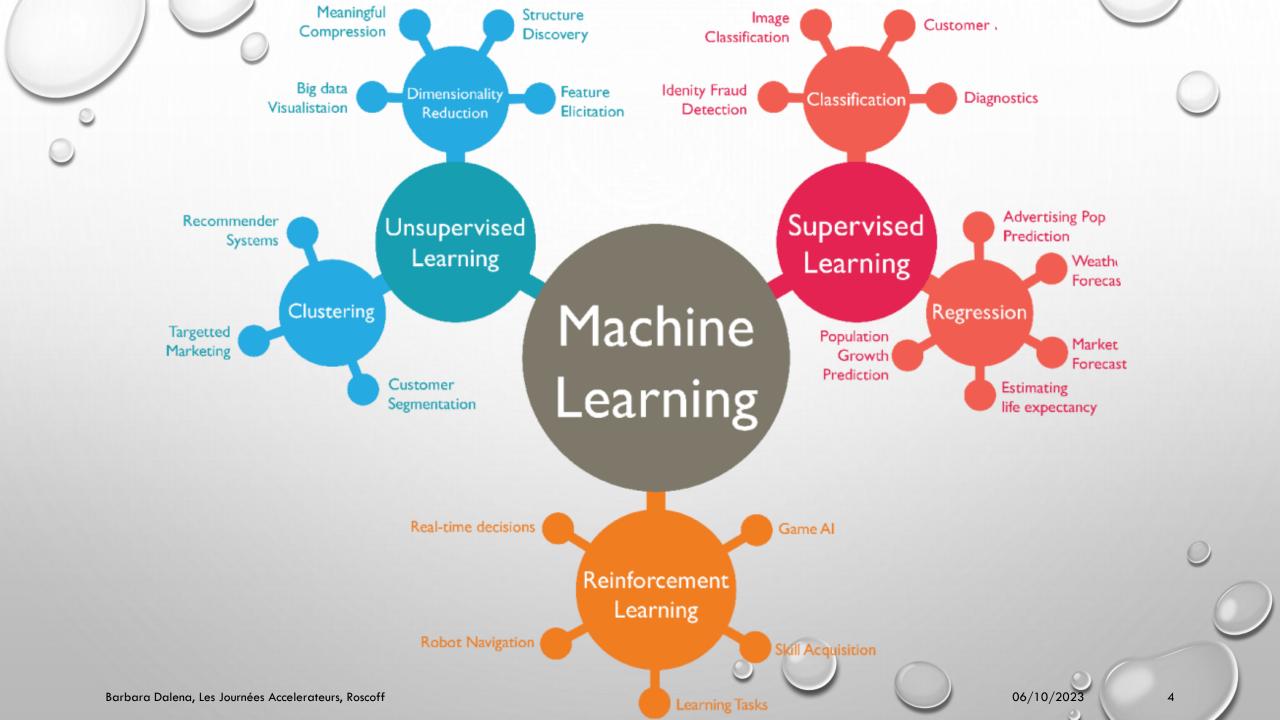
From whom I have taken some of the material for this presentation I. Vidana, G. Valentino, G. Azzopardi, A. Eichler, S. Pioli, A. Edelen, E. Fol, K. Rajput, IDRIS

The list of examples given in this presentation is not exhaustive and is filtered by my personal analysis

OUTLINE

06/10/2023

- Introduction to AI
- Al and Accelerators
 - Anomaly detection
 - Accelerator modeling
 - Accelerator control
- Example of national and international successful applications
- Perspectives



SOME DEFINITION

SUPERVISED LEARNING

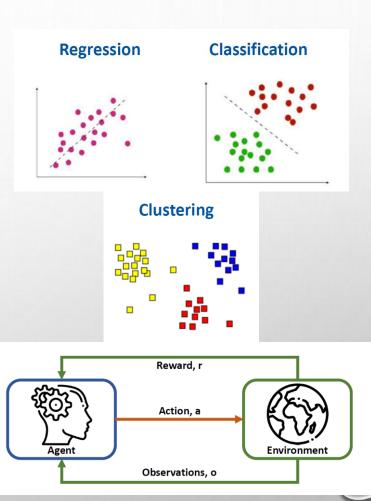
Known input-output (feature-label) relations are given to the machine learning algorithm. Once the model is trained based on the known data, one can use unknown data into the model to get predictions.

UNSUPERVISED LEARNING

The output of the input training data is **unknown**. The input data is fed to the Machine Learning algorithm and is used to train the model which then is employed to **search for patterns in the data**.

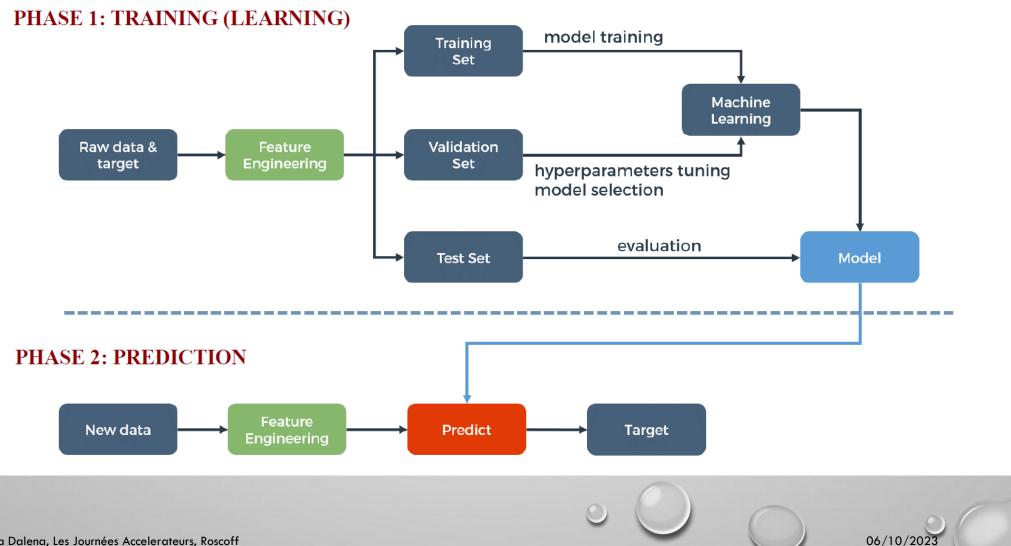
REINFORCEMENT LEARNING

Given a framework of rules and goals, an agent (algorithm) learns in an interactive environment by trial and error using feedback from its own actions and experiences and it gets rewarded or punished depending on which strategy it uses. Each reward reinforces the current strategy, while punishment leads to an adaptation of its policy.



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HOW MACHINE LEARN



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SUCCESS FACTORS

1. DATA

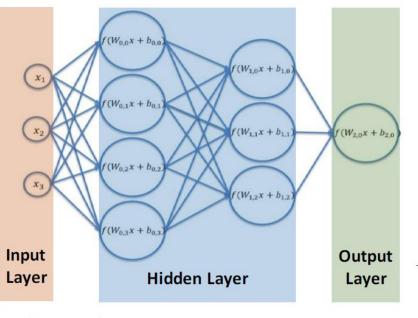
Huge amount of data to train algorithms and new techniques to label them, due to increasing digitization of environments

2. ENVIRONMENT/FRAMEWORK

Facebook, google, Amazon, academic research, start-ups... Software layers: Torch, pyTorch, Keras, Tensorfow, cuda...

3. HARDWARE

CPU, GPU, TPU, FPGA, SuperComputers

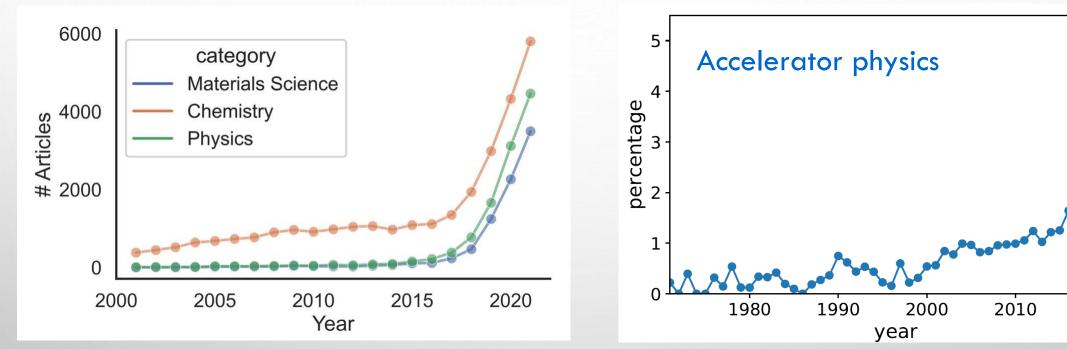


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Neural networks

TREND OF ML IN SCIENTIFIC PUBLICATIONS



https://twitter.com/BenBlaiszik/status/1496509101915967490

Percentage of publication per year related with Al in most common Accelerator Physics journals from OpenAlex https://openalex.org (Courtesy of F. Gargiulo)

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2020

AI AND ACCELERATORS

WHY IS ML USEFUL FOR PARTICLE ACCELERATORS?

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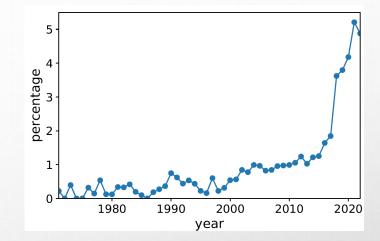
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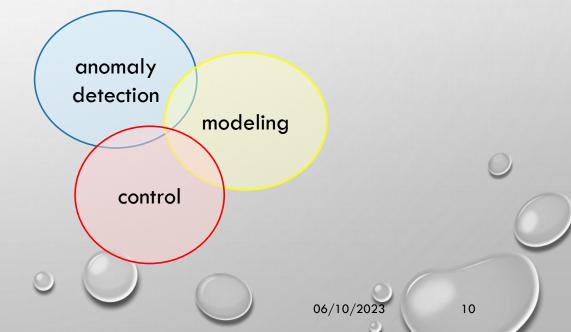
AI AND ACCELERATOR

In US laboratories:

"ML techniques have been applied to particle accelerators since the late 1980s-1990s, for accelerator control and tuning [...] None of these systems were eventually used routinely as part of an accelerator's main control system due to limitations in the then-available hardware, algorithms, and software packages, as well as the limited accessibility of good data sets and simulation tools."

A. Edelen et al., arXiv:1811.03172 [physics.acc-ph]





Machine Learning (ML) can be useful for

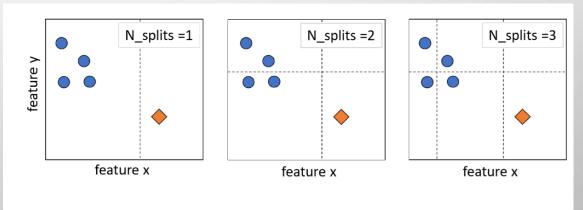
ANOMALY DETECTION

Accelerators are complex objects that require monitoring of many interacting subsystems:

- ML technique can be used to detect precursors of faults
 - Quench of superconductive magnets or superconductive RF cavities faults
 - Beam loss predictions
- Anomaly detection algorithms can also be used to identify bad signals:
 - Bad readings from beam position monitors
 - Assist to automated collimator alignment

 \Rightarrow improve beam quality, machine protection, availability of the accelerator

The less splits are needed, the more "anomalous"



Conceptual illustration of Isolation Forest algorithm

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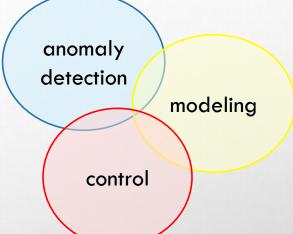
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ACCELERATOR MODELING (SURROGATE MODELS AND OPTIMIZATION ALGORITHMS)

• Existing machine

ML can learn models that combine information from physics-based simulations with measured data

⇒ provides real-time simulations in control rooms to improve beam time and quality (CONTROL)



• Future accelerators

Accurate simulations are essential for the design and the optimization of future machines

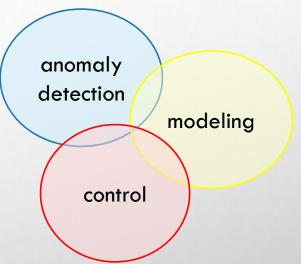
- ML can speed up simulations and reduce CPU time, providing fast surrogate models of non-linear phenomena
- ✓ ML can increase the extend of parameter space optimization for challenging accelerator design problems and allow faster exploration of various competing parameters (see talk F. Massimo and G. Kane)

ACCELERATOR CONTROL

- TUNING, CONTROL
 - Complement and SPEED-UP fine-tuning of machine settings by operators or online optimization routines, and dedicated feedback

VIRTUAL DIAGNOSTICS

- Create new instruments or observations, exploiting correlations between cheap signals and beam quality (see C. Lassalle poster)
- Provide estimate of beam parameters in case of missing instruments
- ADVANCED DATA ANALYSIS
 - Use image data, clustering and correlations algorithms to automatically detect beam losses, aberrant behavior, classify quench or modes of beam instabilities (ANOMALY DETECTION)



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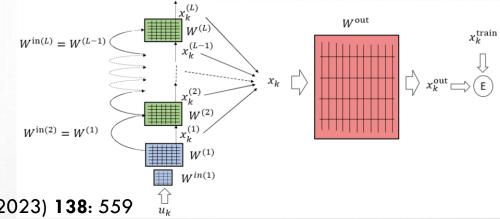
EXAMPLE OF NATIONAL AND INTERNATIONAL SUCCESSFUL APPLICATIONS

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APPLICATION TO BEAM PHYSICS

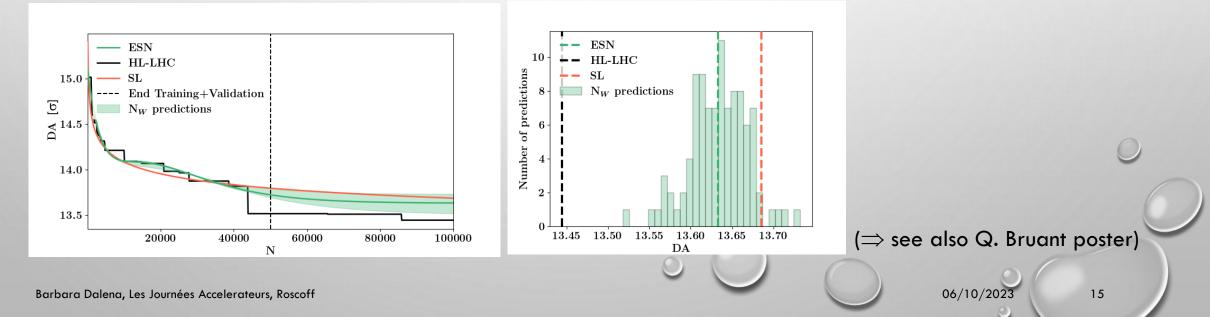
Reservoir Computing networks models and replicates the time evolution of Dynamic Aperture, allowing to speed–up tracking simulations for high energy hadron storage rings.



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M. Casanova, B.D. et al., Eur. Phys. J. Plus (2023) 138: 559

Echo State Networks



ANOMALY DETECTION ANALYSIS

Isolation Forest with **decision tree** is used by at **CERN** to detect faulty BPMs signals that remain after SVD cleaning of turn by turn **optics measurements data**.

E. Fol et al. WEPGW081 IPAC 2019

IP2 IP3 IP4 IP5 IP8 IP1 IP6 IP7 0.2 SVD SVD and Isolation Forest 0.1 $\Delta \beta_X / \beta_X$ -0.1-0.25000 10000 15000 20000 25000 0 Longitudinal location [m]



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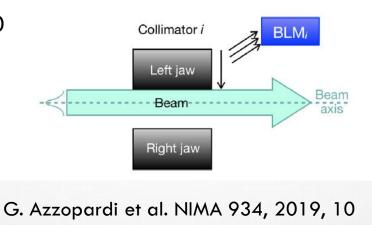
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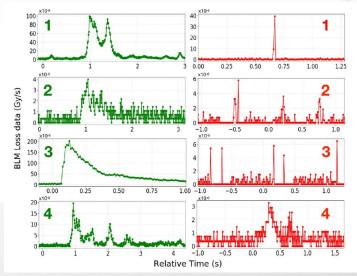
K-mean, Density-Based Spatial Clustering and Isolation Forest in combination with PCA is used by F. Poirier et al. at ARRONAX Cyclotron to **identify anomalies** that occur for nonlabelled multi-variate data **during radio-isotopes production**.

F. Poirier et al. TUPM036 IPAC2023

AUTOMATED ANOMALY DETECTION

Establish the operational settings of ~100 LHC collimators by automatically detect true and false alignment-spikes. Successfully deployed in operation with a gain of a factor three in alignment time.





Errant beam prediction at SNS accelerator

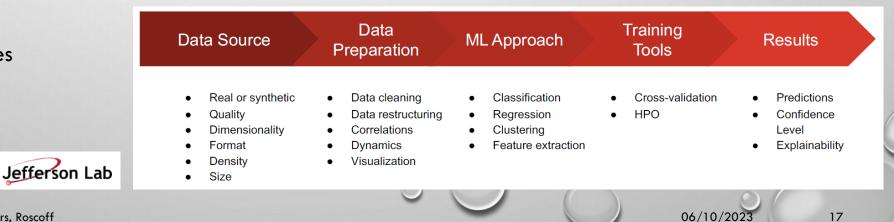
L-Università

ta' Malta

- Predict an upcoming machine trip before it occurs to potentially allow the crew to change settings to avoid it
- Use pulses leading to a trip (tagged "Before") and identify features that indicate an upcoming failure
- Data science pipeline:

identify accelerator failures with > 80% accuracy

K. Rajput



CAK RIDGE

OPTIMIZATION IN CONTROL ROOM

Machine Learning Frameworks/tools for accelerators:

Xopt+BADGER (SLAC)

- For simulations (models) or experiments (data)
- Independent of optimization algorithm + easy to incorporate custom algorithm
- Provides interface for operation in control room

⇒ Used at ESRF in collaboration with DESY, LNBL and SLAC for tuning of the EBS storage ring lifetime and injection efficiency with Bayesian techniques (S.Liuzzo et al., MO3AO01, ICALEPCS 2023)

GeOFF and the Machine Learning Platform (CERN)

Framework for operational use of RL and numerical optimization

- provide ecosystem for accelerator optimization and control
- provide compatibility with as many algorithms as possible
- facilitate the progression manual tuning \rightarrow numerical optimization \rightarrow machine learning

 \Rightarrow Used at CERN for almost all accelerators (see talk A. Lasheen)

EURO-LABS project supports efforts towards agnostic usage and portability

TOWARDS AN AUTONOMOUS ACCELERATOR

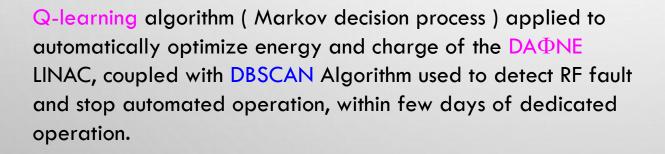
Autonomous operation of FLUTE, ARES LINACs

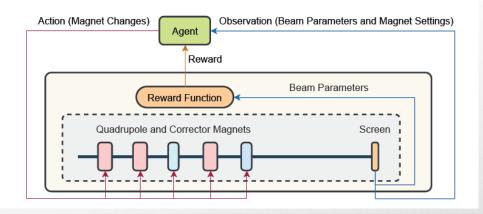
Deep Deterministic Policy Gradient algorithm and Twin Delayed Deep Deterministic policy gradient demonstrate ability to solve beam optimization tasks on simulated data.

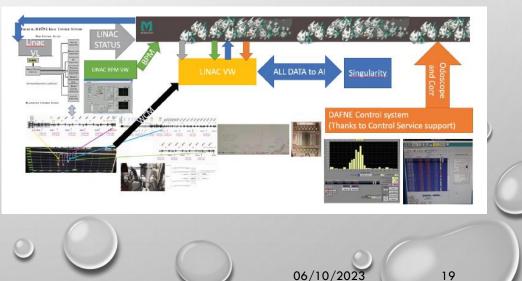




S. Pioli et al. THAL03 ICALEPCS 2021







PERSPECTIVES

WHAT CAN WE DO MORE ?

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EXAMPLE: INTHEART



• Les objectifs :

- Partager les connaissances et appréhender les nouvelles techniques en IA
- Discuter et travailler ensemble à travers un groupe ouvert, transverse au CEA et au-delà
- Participants (~150 personnes):
 - CEA : DAM, DES, DRF, DRT
 - o CNRS
 - Université Paris-Saclay
- Financement PTC (Programme Transverse de Compétence CEA)
- Pour y participer/contribuer : Valerie.gautard@cea.fr



- Des seminaries (https://indico.in2p3.fr/event/17858/page/2883-2022)
- Des formations
- > Des workshops
- Web sites: IntheArt : https://indico.in2p3.fr/event/17858/page/1967-intheart GitLab : https://drf-gitlab.cea.fr/InTheArt

Redmine : https://forge.in2p3.fr/projects/intheart?jump=welcome

Coutesy of V. Gautard

Barbara Dalena, Les Journées Accelerateurs, Roscoff

A NEW SYNERGETIC APPROACH

- Unlock the use of artificial intelligence in particle and nuclear accelerators as well as in light/neutron sources;
- Tackle all challenges of particle accelerators.

A French network: M4CAST

Multiphysics Modeling, Machine learning and Model-based Control in Accelerators Science and Technology

A European network: TRAINABLE

TowaRds An International network for multiphysics modelling, machine learning And model-Based control in accelerator sciences and technoLogiEs

target an Horizon Europe project ARTIFACT

ARTificial Intelligence For Accelerators, user Communities and associated Technologies



CNRS

Barbara Dalena, Les Journées Accelerateurs, Roscoff

Courtesy of A. Ghribi

STRATEGY

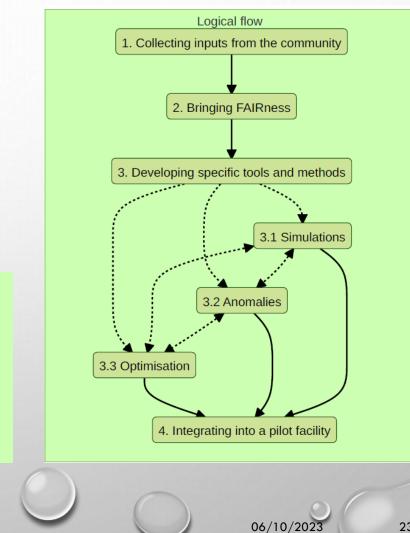
Transverse flow

Training and knowledge transfer

Industrial applications and technology transfer

Interdisciplinarity and outreach

- Guidelines to unclock the use of Al in accelerators ٠
- Standardize and open our data and approaches ٠
- Structure ourselves to work in a fertile collaborative space ٠
- Transfer links (astrop, HEP, medecine, ...) ٠
- Training: students as well as professionals •



Courtesy of A. Ghribi

TOWARDS A MORE SUSTANAIBLE DEVELOPMENT

Outcomes:

- Enhance scientific competitiveness of Research Infrastructures (RI)
- Enhanced RI capacities to address research challenges and EU policy priorities ;
- o Increase collaboration of research infrastructures with universities, research organization and industry
- Increase of technological level of industries
- Integration of research infrastructures into local, regional and global innovation systems and promotion of entrepreneurial culture

THANK YOU

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