Machine Learning for Earth and Climate Sciences

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Earth science
Earth observation
Deep learning

Reichstein, Camps-Valls et al, Nature, 2019
Camps-Valls, Tuia, Xiang, Reichstein. Wiley & Sons book, 2021
Prediction of crop yield from space
How is our coastline and ocean?
What about our atmosphere and air quality?
Some machine learning applications

One soil map
https://map.onesoil.ai

Global wealth map
http://penny.digitalglobe.com

Flood analyzer
http://floods.wri.org

Disease mapping
https://www.healthmap.org
AI opportunities
Neural networks for spatio-temporal classification

- Convolutional neural nets (CNN): hierarchical structure exploits spatial relations
- Long short-term memory (LSTM): recurrent network that accounts for memory/dynamics

“A Deep Network Approach to Multitemporal Cloud Detection”
Probabilistic and scalable classifiers

- Gaussian processes as an alternative to neural nets
- GPs allow a probabilistic treatment, confidence intervals, feature ranking, deep too!
- Gaussian processes start to be scalable ...

Multitask learning

- Multiple inter-related outputs? Data from multiple sources?
- Learn to fuse heterogeneous information

“Multitask Remote Sensing Data Classification”
Spatio-temporal variable prediction

- STA is common place in climate informatics, neuroscience, video processing, NLP, ...
- **Current approaches:** CNN + LSTM, space-time Gaussian processes
- **Novel approaches:** distribution regression and variational deep GPs

\[
P \mapsto \mu_k(P) \rightarrow P \mapsto [E\phi_1(X), \ldots, E\phi_s(X)] \in \mathbb{R}^s
\]

\[
\langle \mu_k(P) ; \mu_k(Q) \rangle_{\mathcal{H}_k} = E_{X \sim P, Y \sim Q} k(X, Y)
\]

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“Nonlinear Distribution Regression for Remote Sensing Applications”
Adsuara, Perez,Muñoz, Mateo, Piles, Camps-Valls, IEEE TGARS 2019

“A Survey on Gaussian Processes for Earth Observation Data Analysis”

“Deep Gaussian Processes for Retrieval of bio-geo-physical parameters”,
Google Earth Engine

Remote Sensing

Multitemporal Cloud Masking in the Google Earth Engine

Gonzalo Mateo-García and Gustau Camps-Valls

Global Estimation of Biophysical Variables from Google Earth Engine Platform

Manuel Camps-Taberner and Gustau Camps-Valls

A methodology to derive global maps of leaf traits using remote sensing and climate data

Álvaro Moreno-Martínez, Gustau Camps-Valls, Jens Knagge, Nathaniel Robinson, Markus Reichstein, Peter van Bodegom, Roes Kramer, J. Hans C. Cornelissen, Peter Reich, Michael Bahn, Ulo Nümmets, Josep Prats-lleonart, Joseph M. Craine, Bruno E.L. Cerabolini, Vanessa Minden, Daniel C. Laughlin, Lawren Sack, Brady Allred, Christopher Baraloto, Checho Byun, Nadejda A. Soonzlovskai,a, Steve W. Running
Potential risks and challenges
ML in Earth science rocks... *only* when some things happen!

- Strong spatial and temporal correlations
- Big data accessible
- Cheap computing resources available
- Fast scalable ML models available
- *No expert knowledge needed*
- High prediction accuracy is enough
- Understanding the system is not that relevant
Machine/deep learning challenges

- Do Models respect Physics Laws? **Physics-aware ML**
- What did the ML model learn? **Explainable AI (XAI)**
- Do they get cause-effect relations? **Causal discovery and inference**
There is light at the end of the tunnel.
### Explainable Artificial Intelligence (XAI)

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**A Survey on Explainable Artificial Intelligence (XAI): towards Medical XAI**, Tjoa 2019


<table>
<thead>
<tr>
<th>Methods</th>
<th>HSI</th>
<th>ANN</th>
<th>Mechanism</th>
</tr>
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<tbody>
<tr>
<td>CAM with global average pooling</td>
<td>X</td>
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<tr>
<td>+ Grad-CAM</td>
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<td>+ Guided Grad-CAM and Feature Occlusion</td>
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<td>+ Respond CAM</td>
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<td>+ Multi-layer CAM</td>
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<tr>
<td>LRP (Layer-wise Relevance Propagation)</td>
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<td>N.A.</td>
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<tr>
<td>+ Image classifications. PASCAL VOC 2009 etc</td>
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<tr>
<td>+ Audio classification. AudioMNIST</td>
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<td>+ LRP on DeepLight. IMRI data from Human Connectome Project</td>
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<td>+ LRP on CNN and on BoW (bag of words) SVM</td>
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<td>+ LRP on compressed domain action recognition algorithms</td>
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<td>+ LRP on video deep learning. selective relevance method</td>
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<td>+ BiLRP</td>
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<td>Slot Activation Vectors</td>
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<tr>
<td>PRM (Peak Response Mapping)</td>
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<tr>
<td>LIME (Local Interpretable Model-agnostic Explanations)</td>
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<tr>
<td>+ MUSE with LIME</td>
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<tr>
<td>+ Guideline-based Additive Explanation optimizes complexity, similar to LIME</td>
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<td># Also listed elsewhere: [55], [68], [70], [73]</td>
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<td>Others. Also listed elsewhere:</td>
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<td>+ Direct output labels. Training NN via multiple instance learning</td>
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<td>+ Image corruption and testing Region of Interest statistically</td>
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<td>+ Attention map with autofocus convolutional layer</td>
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<td>DeconNet</td>
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<td>Inverting representation with natural image prior</td>
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<td>Inversion using CNN</td>
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<tr>
<td>Guided backpropagation</td>
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<tr>
<td>Activation maximization/optimization</td>
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<td>+ Activation maximization on DBN (Deep Belief Network)</td>
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<tr>
<td>+ Activation maximization, multifaceted feature visualization</td>
<td>✓</td>
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<td>Visualization via regularized optimization</td>
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<td>Semantic dictionary</td>
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<tr>
<td>Decision trees</td>
<td>N.A.</td>
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<tr>
<td>Propositional logic, rule-based</td>
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<tr>
<td>Sparse decision list</td>
<td>✓</td>
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</tr>
<tr>
<td>Decision sets, rule sets</td>
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<tr>
<td>Encoder-generator framework</td>
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<tr>
<td>Filter Attribute Probabilistic Density Function</td>
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<tr>
<td>MUSE (Model Understanding through Subspace Explanations)</td>
<td>✓</td>
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</tbody>
</table>

**Decomposition**

**Saliency**

**Perceptive Interpretability**

**Signal**

**Inversion**

**Optimization**

**Verbal**
Physics-aware ML

- A. Data-model blending
  Joint Gaussian processes
  Distribution regression

- B. Surrogate modeling
  Gaussian processes
  Bayesian optimization

- C. Learning to parameterize
  Variational inference
  Monte Carlo, Gibbs

- D. Learning physics
  Sparse regression
  Latent force models

PERSPECTIVE

Deep learning and process understanding for data-driven Earth system science

Markus Reichstein1,2#, Gustau Camps-Valls3, Bjorn Stevens4, Martin Jung5, Joachim Denzler1,5, Nuno Carvalhais1,4 & Prabhat7

Machine learning approaches are increasingly used to extract patterns and insights from the ever-increasing stream of geospatial data, but current approaches may not be optimal when system behaviour is dominated by spatial or temporal context. Here, rather than amending classical machine learning, we argue that these contextual cues should be used as part of deep learning (an approach that is able to extract spatio-temporal features automatically) to gain further process understanding of Earth system science problems. Improving the predictive ability of seasonal forecasting and modelling of long-range spatial connections across multiple timescales, for example. The next step will be a hybrid modelling approach, coupling physical process models with the versatility of data-driven machine learning.


“Living in the Physics - Machine Learning Interplay for Earth Observation”
**Causality**

Inferring causation from time series in Earth system sciences


**Diagram:**

- Granger causality
- Nonlinear state-space methods
- Causal network learning algorithms
- Structural causal models

**Abstract:** Establishing causal relations between random variables from observational data is perhaps the most important challenge in today’s science. In remote sensing and geosciences, this is of special relevance to better understand the Earth’s system and the complex interactions between the governing processes.

With societal, economical, and environmental challenges, such as climate change [21,31], there is an urgent need for tools that help us to observe and study the earth system. Nowadays, machine learning and signal processing play a crucial role in this endeavor.

ELLIS, ELISE and AIDA
ELLIS.eu

- ELLIS: European Laboratory for Learning and Intelligent Systems
- Distributed center of excellence in AI
- ELLIS goals and mandates:
  - Coordinates research, fosters collaborations with industry and users, promotes technology adoption, support PhD fellowships & postdoc visits/stays, organize focused workshops
- ELLIS legacy:
  - Place Europe in the global map of top AI research and transfer to industry
  - Make Europe an international talent magnet, incubator of innovation, and ecosystem
- Largely multidisciplinary & organized in Research Programs:
  - Robotics, robustness, health, language processing, earth, etc.

https://ellis.eu
ELLIS is Largely multidisciplinary & organized in Research Programs:
- Robotics, robustness, health, language processing, etc.

“Machine learning for Earth and climate sciences” (Dir.: Gustau Camps & Markus Reichstein)
- **Goal:** Model & understand the Earth with Machine Learning and Process Understanding
  - Spatio-temporal anomaly and extreme events detection, anticipation and attribution
  - Data-driven dynamic modelling and forecasting
  - Hybrid modeling: linking physics and machine learning models
  - Causal inference, Learning and explaining feature representations
  - Earth and Climate model emulation, generative modelling and data-model fusion
- 20 ELLIS Fellow members, regular meetings/workshops, exchange students, teaching material

Universitat de València is a core center in the ICT-48 project **ELISE**

[Link to ELISE website](https://www.elise-ai.eu/)
AIDA - AI Doctoral Academy

- All ICT-48 networks (AI4Media, ELISE, HumanE-AI NET, TAILOR) + VISION consortium joined forces
- New joint instrument to support world-level AI education and research programme
- AIDA offers:
  - access to resources, knowledge & expertise for the latest developments and trends on AI research and innovation
  - operate as an umbrella organisation for AI PhD and Postdoc studies
  - support a new generation of alumni
  - enhance networking and collaboration among talented researchers
  - provide access to workshops/conferences, short courses, mobilities, training/job opportunities

https://www.i-aida.org/
Conclusions
Take-home message

- AI is a paradigm shift
  - Excel in classification, (change) detection, parameter retrieval
  - Automate & understand processes
- Challenges: interpretability + causal relations + physics consistency
- Future:
  - User-centric AI + trustworthiness + accountability
  - Holistic & interdisciplinary education

“Towards a Collective Agenda on AI for Earth Science Data Analysis”

“Living in the Physics - Machine Learning Interplay for Earth Observation”