Comment développer des outils d’apprentissage automatique pour les géosciences ?
Un aperçu de différents usages de réseaux de neurones convolutifs.

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Intérêt des géoscientifiques pour l'IA / machine learning
**Machine learning: what is it?**

1) **database collection**
   Use information from existing examples ...

2) **training**
   ... to learn from them patterns or relations ...

3) **prediction**
   ... that can then be applied to new examples
Artificial Intelligence and Machine learning

- Convolutional neural network
- Multi-layer perceptron
- Deep learning
- Machine learning
- Artificial intelligence
- Robotics
- Logical systems
- Linear regression
- Random forest
- SVM

GPS time series for characterizing earthquakes (and SSEs)
Machine learning: what for?

- *Big data*: data is often easy to collect
- But we don’t always know the relations between variables (ex. physics)
- ML = algorithm that will learn from the data directly

**Machine learning model = function approximation**

\[
\text{input } x \quad \rightarrow \quad \text{function } f \quad \rightarrow \quad \text{output } y = f(x)
\]
Where is it used today?

- Natural language processing: translation
- Image detection
- Image segmentation
- Personalised advertising
- Protein unfolding
And in geosciences?

Remote sensing processing

El Nino prediction

Seismic inversion

Tropical cyclone trajectory prediction

Earthquake detection
Outline

1. Introduction to Machine Learning
2. Convolutional Neural Networks
3. GPS time series for characterizing earthquakes (and SSEs)
Convolutional neural network

\[ f_\theta(img) = \text{output} \]

- Suited for image-like data
- Non-linear/complex relationships
Temporal coherence
InSAR matrix classification
Marie-Pierre Doin,
Salah-Eddine Boudaour (M2)

Optical image correlation for deformation estimation
James Hollingsworth,
Tristan Montagnon

03.01.2019 Landsat 8 images 17.01.2019
Outline

1. Introduction to Machine Learning

2. Convolutional Neural Networks

3. GPS time series for characterizing earthquakes (and SSEs)
GPS time series for characterizing earthquakes (and SSEs)

ERC Deep-Trigger - Anne Socquet

Giuseppe Costantino (PhD)
GPS time series for characterizing earthquakes (and SSEs)

- Learn from synthetic database (20 K samples)
- Okada dislocation model + realistic noise
Data: list of time series

→ 1D convolutional neural network
Data: list of time series

→ 1D convolutional n. network

adapted from Van der Ende & Ampuero, 2020
Data: list of time series

\[ \rightarrow 1D \text{ convolutional n. network} \]

interpolated images

\[ \rightarrow 2D \text{ convolutional n. network} \]

adapted from Van der Ende & Ampuero, 2020
Data: list of time series

> 1D convolutional network

interpolated images

> 2D convolutional network

image time series

> 2D CNN + transformer

adapted from Van der Ende & Ampuero, 2020
Suite de la session:

- **Introduction et machine learning pour problèmes 2D**

- **Détection de séismes (1D CNN) et interprétabilité**
  
  *Josipa Majstorović*

- **Détection de signaux sismologiques précoces par IA**
  
  *Kevin Juhel*
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Data and methodological scope, includes:
- Machine learning; Artificial intelligence; Statistics; Data mining
- Computer vision; Econometrics
- Data science, broadly defined.

Environmental scope, includes:
- Water cycle, atmospheric science (including air quality, climatology, meteorology, atmospheric chemistry & physics, paleoclimatology)
- Climate change (including carbon cycle, transportation, energy, and policy)
- Sustainability and renewable energy (the interaction between human processes and ecosystems, including resource management, transportation, land use, agriculture and food)
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- Societal impacts (including forecasting, mitigation, and adaptation, for environmental extremes and hazards)
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