WELCOME TO THE TRA 6 LECTURE SERIES INNOVATION PATHWAYS TO SUSTAINABILITY

ARTIFICIAL INTELLIGENCE AND DATA SCIENCE IN EARTH OBSERVATION - HELP SHAPING A SUSTAINABLE FUTURE

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Artificial Intelligence and Data Science in Earth Observation – Help Shaping a Sustainable Future

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ESA-DEVELOPED EARTH OBSERVATION MISSIONS

Satellites
25 under development
14 in operation

Science
Copernicus
Meteorology
EO = Big Data

Data Volume in DLR’s EO Archive

PB


Today
Earth Observation for a Sustainable Future

We research and develop solutions for major challenges in the following areas ...

- Earth System Research and Environmental Sciences
- Global Change Research
- Meteorology
- Sustainable Development
- Security
- Mobility
- Resource Management
- City Planning
NO2 Concentration Before and During Corona Lockdown 2020
Why Do We Need AI and Data Science?

- user domain
- information retrieval
- observation systems
AI and Data Science in Earth Observation

Explorative Signal Processing Methods

Date Fusion

Information Mining

Machine Learning/Deep Learning

Big Data Management and HPC
Two EO Data Science Stories

AI4EO
Deep Learning in Remote Sensing

Applications on Sustainability
Global Urban Mapping
Deep Learning is the driver of today’s breakthroughs in AI!

Source: B. Aunkofer
Machine Learning/Deep Learning

Classical Neural Net
mid 1980s

Deep Neural Net
since 2006/2012
Papers Related to Deep learning in Remote Sensing

[Source: Scopus]

Status: October 25th, 2020
What makes Deep Learning in Earth Observation Special?

- Classification and detection are only small fractions of EO problems

- Focus on retrieval of physical or bio-chemical variables
  - High accuracy requirements (data generation is expensive)
  - Traceability and reproducibility of results
  - Quality measures (error bars, outlier flags,...) indispensable

- Decadal expert domain knowledge available

- Well-controlled data acquisition (radiometric, geometry, spectrometric, statistical, SNR,...)

- Data can be 5-dimensional (x-y-z-t-λ), complex-valued and multi-modal:
  - SAR
  - Lidar
  - multi-/super-/hyperspectral
  - GIS, OSM, citizen science, social media,...

- Often: lack of sufficient training data
Our Deep Nets Zoo
Hyperspectral Image Analysis
Unsupervised Spectral-Spatial Feature Learning via Deep Residual Conv-Deconv Net

Unsupervised Spectral-Spatial Feature Learning via Deep Residual Conv-Deconv Net

Application I: Classification

Application II: “Free” Object Localization

We found some neurons in our network own good description power for semantic visual patterns in the object level. For example, the neurons \#52 and \#03 can be used to precisely capture metal sheets (left), and vegetative covers (right).

Hyperspectral Classification with High Intra-class Variability

(a) Spectral Signatures with Spectral Variability
Time Series Data Analysis
Recurrent Convolutional Neural Network for Change Detection

Mou, Bruzzone, Zhu, IEEE TGRS 57 (2), pp. 924-935, 2019
Recurrent Convolutional Neural Network for Change Detection

Location: Taizhou City, China
Legend: Changed areas (in binary change detection); city expansion; soil change; water change

Mou, Bruzzone, Zhu, IEEE TGRS 57 (2), pp. 924-935, 2019
Global Applications with Sentinels
Global Cloud Cover – 67%

Image: ESA/Cloud-CCI
cGAN for Removing Clouds from Sentinel-2 Data using Cloud-free Radar Data

**Motivation:** Optical sensors cannot penetrate clouds, but microwaves do.

**Objective:** Train generative adversarial network to produce cloud-free optical imagery

Grohnfeld et al., 2018; Meraner et al., 2020, Ebel et al. 2020.
Cloud Removal Using Sentinel-1 Images – Results

Sentinel-2 input (corrupted by haze or clouds)  Sentinel-2 input (ground truth)  SAR-Opt-cGAN result (Input: Sentinel-1 & Sentinel-2)

Sentinel-2 True-color composition:
Red = Band 5
Green = Band 3
Blue = Band 2

Sentinel-2 SWIR-color composition:
Red = Band 8A
Green = Band 11
Blue = Band 12
Citizen Science
Global Tweets

c. 300 million precisely geolocated tweets
Analysing Sentiments in Multilingual Geotagged Tweets related to COVID-19 in Europe Countries

Kruspe et al., ACL, 2020
Audiovisual Reasoning in Earth Observation
What’s Next?
Our Methodological Research Agenda

- Re-implant physics, Bayes and domain expertise
- Reasoning
- Transferability
- Uncertainty
- Explainability
- Deep topology learning
- Quantum Computing in AI
- Ethics
NN architecture and loss function
+ trainings data
(+ training algorithm)
(+ initialization)
= DL algorithm
So2Sat LCZ42 Dataset – Global Local Climate Zones Classification

Annotated cities

Labeling confidence

Download

Zhu et al., IEEE GRSM, 2020
Key Features

• 400,673 pairs of Sentinel-1/2 image patches with LCZ labels and labeling confidence

• Hand labelled 42 cities covering 10 culture zones

• Data:
  • Sentinel-1
  • Sentinel-2, seasonal

• 10 independent votes for a rigorous labelling quality assessment

• Suitable benchmark for:
  • Image classification
  • Data fusion
  • Quantification of uncertainties
  • Computing in AI
  • Automatic Deep Topology Learning
SEN12MS-CR – A Large Scale Benchmark for Cloud Removal

Ebel et al., IEEE TGRS, 2020
Key Features – SEN12MS-CR

114,325 triplets of 256x256-pixel patches of dual-pol Sentinel-1 data, clear-sky multi-spectral Sentinel-2 images, and cloudy Sentinel-2 images.

- Data sampled from 169 scenes
- located all across the globe & across every season

- Data covers a wide range of cloud coverage:
  - clear view, semi-transparent clouds, thick & dense clouds
  - (cloud coverage: 47.93 ± 36.08 %)
ERA – Benchmark for Event Recognition in Aerial Videos
2,896 aerial videos in 25 event classes
Urban Growth Happens Mostly in Developing Areas

World City Populations 1950-2030

Circle areas proportional to city populations in:

- **1950**
- **1990**
- **2015**
- **2030**

Cartography: D. A. Smith, CASA UCL.
Open Science – Open Data?

> 3 Billion buildings in the world

358 Million building footprints in OSM < 12%

Only 3% buildings in OSM have height information with big errors (5 m) < 0.4 %
Global Building Footprints?
Building Footprint Extraction from *NewSpace*-Satellite Images

A Graph Convolutional Recurrent Neural Network trained with satellite image and GIS building footprint pairs from 74 cities.
Site: Lagos, Nigeria
Site: Lagos, Nigeria
How about Changes?
01.08.2020
Beirut, Lebanon
Mapping Every Building in 3D?
Signal Processing Algorithms

X-Ray of the Earth

Deep Learning Algorithms

Building heights

Building shapes
First Impression of the Global 3D Urban Models
accuracy better than 2m
Understanding Semantics?
Caracas (Petare), Venezuela

Reference
Nairobi (Kibera), Kenia
Large-Scale-Poverty (LSP) Dataset:
- 4186 slums
- Total slum area 234.3 km$^2$
- Mean slum size 11.76 ha

Transfer learn pretrained XFCN to a specific geographic region.

Stark et al, JSTARS, 2020
Mumbai, India
F1 86,98%
Nairobi (Kibera), Kenia
F1 83.24%
10 Petabytes → buildings in 3D, settlement types, morphological structures, population density, and their evolutions over time.
Munich – A Gravity Center of AI4EO
BMBF “International Future Labs for Artificial Intelligence”

Artificial Intelligence for Earth Observation: Reasoning, Uncertainties, Ethics and Beyond

Acronym: AI4EO

Future Lab AI4EO
Munich, Germany

13 guest professors
70 young talents
Which will the Twitter algorithm pick – Mitch McConnel or Barack Obama?
Tony “Abolish (Pol)ICE” Arcieri 🦅 @bascule · Sep 20

Trying a horrible experiment...

Which will the Twitter algorithm pick: Mitch McConnell or Barack Obama?
Ethics in AI4EO

- fundamental norm
- social norm
- various sector
- different group
- greater attention
- greater control
- improved image resolution
- responsible AI4EO
- central relevance
- individual human value

- ethical framework
- data portability
- new European general
- AI uptake
- economic study
- process of reflection
- inclusive development

- privacy
- equality
- human value
- data protection
- fairness

- ethical issues
- inclusive process
- general data protection
- algorithmic bias
- technological development

- satellite image
- level of data
- European general data
- early stage
- data protection regulations
- study of ethics
- use of AI
- challenge of ethics
- societal level

- DLR
- TUM
Our Mission

“The Future Lab AI4EO” brings **20 renowned international organizations** across 9 countries and **29 highly ranked scientists at professor level** together to address three fundamental challenges in Earth observation specific cutting-edge artificial intelligence research – **Reasoning, Uncertainties, and Ethics.**

We offer **70 Beyond Fellow Scholarships** for a funded research stay in our lab.

Our goal is to not only **advance Earth observation science** but also make key contributions for the **interpretability of AI and its ethical implications**, and towards **AI4EO technology transfer.**
AI4EO Beyond Fellowship

We offer:
3~6 months research stay in our lab

Selection criteria:
an innovative AI4EO topic;
a talented individual

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