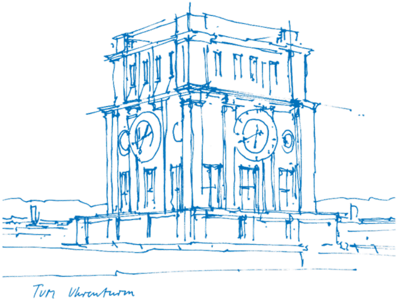
Earth Observation and Machine Learning

From Language Model to Earth Model

Marc Rußwurm M.Sc., advised by Dr. Marco Körner

Technical University of Munich, Germany
Remote Sensing Technology

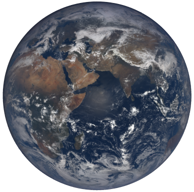
May 3rd 2019, OATML-Lab, Oxford, UK



About

Background

Earth Observation



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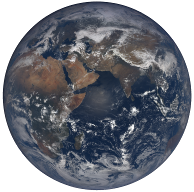

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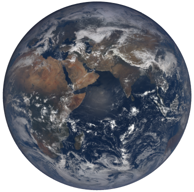

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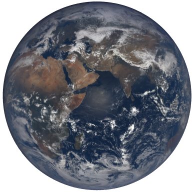

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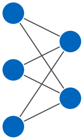

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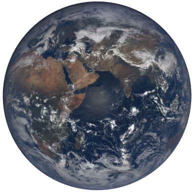

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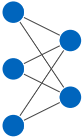
Machine Learning



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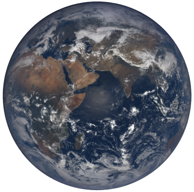

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Early Classification of Time Series

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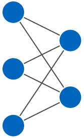


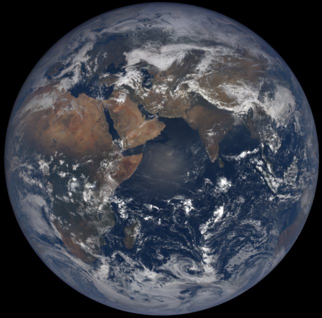
This Talk

Organized in three parts

Part I Overview Earth Observation

Part II Research and Projects

Part III Workshops and Programs around EO and ML



Part I: Earth Observation

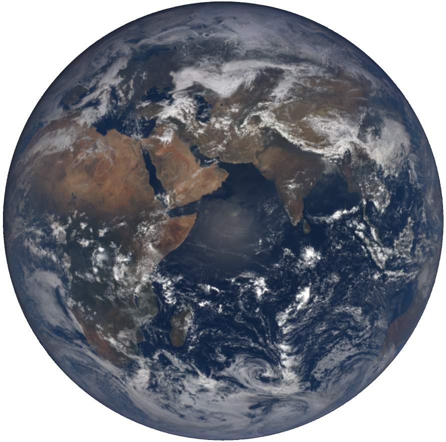
System Earth

Partially measuring System Earth

$\boldsymbol{X} =$  ()

knowledge extraction through pattern recognition and machine learning

$$? = f(\boldsymbol{X})$$



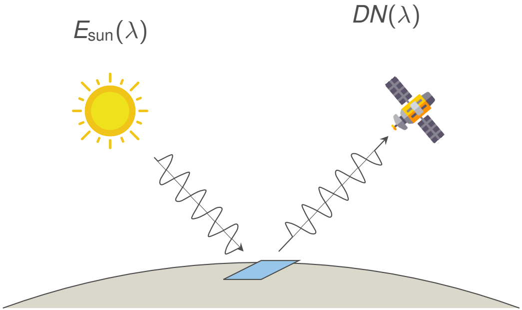
Passive Optical Sensors

Sensor measures **Digital Numbers** DN(λ) for each band wavelength λ.

Digital Numbers are normalized to **Radiance** $L(\lambda)$, $\left[\frac{W}{srm^1}\right]$ by gain and offset calibration.

Radiance is normalized to **top-of-atmosphere reflectance** $\rho(\lambda)$

Bottom-of-atmosphere reflectances are reconstructed using a functional model of the atmosphere.



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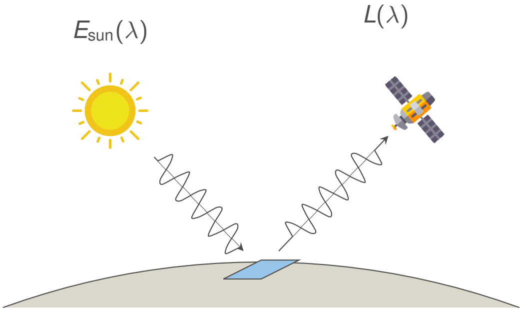

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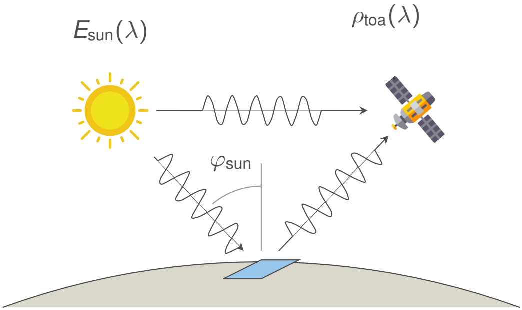

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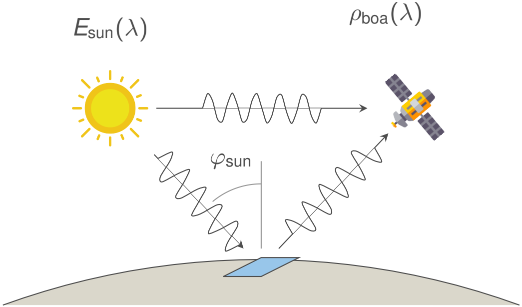
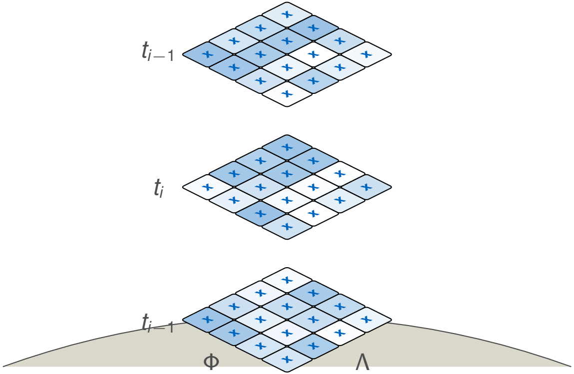


Spatial and Temporal Discretization

$$\boldsymbol{X} = \begin{pmatrix} \rho_{\lambda_1} \\ \rho_{\lambda_2} \\ \dots \\ \rho_{\lambda_n} \end{pmatrix}$$

Spectral reflectance of **spectral bands** disctretized on a **spatial grid**. Each grid cell is georeferenced by its Longitude Λ and Latitude Φ. Acquisitions in regular **temporal intervals**.



Hands-on: Optical Earth Observation

Weather Satellites

At the Langrange 1 Point

dscovr:epic

8 km spatial resolution

image every 20s

10 spectral channels

twitter.com/dscovr_epic epic.gsfc.nasa.gov

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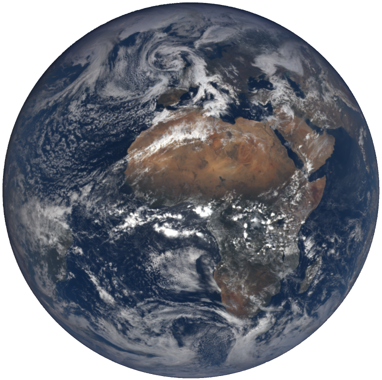

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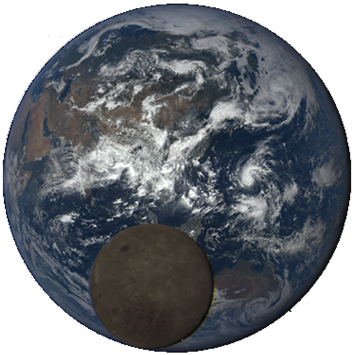

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Weather Satellites

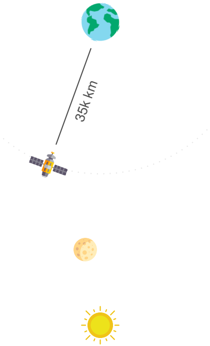
At geostationary orbit

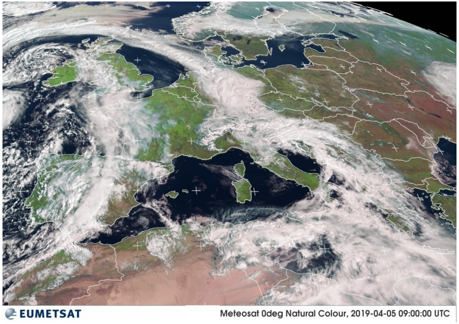
MeteoSAT, GOES

2.5 - 5km km spatial resolution

image every 15 minutes

12 spectral 0channels





`http://oiswww.eumetsat.org`

Icons from `https://www.flaticon.com`

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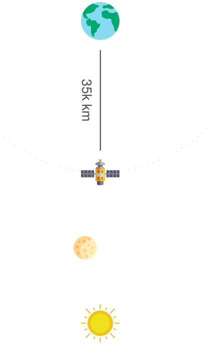

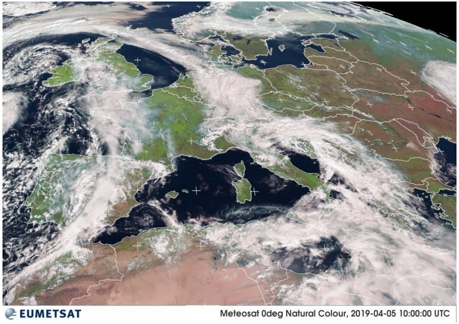

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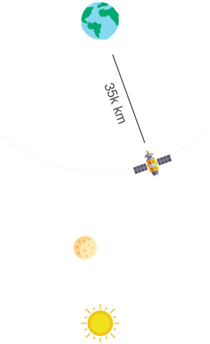

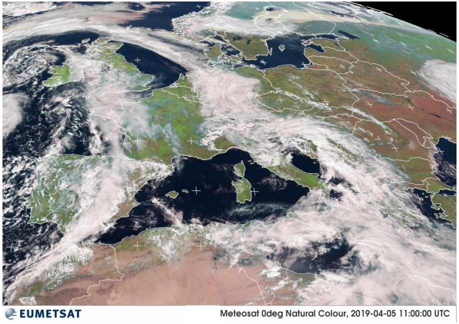

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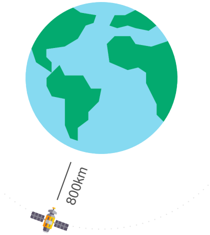
Sun Synchronus Orbit

Environmental Satellites with 1km spatial resolution every day

- NASA's MODIS Aqua/Terra
- ESA's Sentinel 3

Multi-spectral satellites with 10-60m spatial resolution 3-10 days

- NASA's Landsat Satellites (since 70s!)
- ESA's Sentinel 2



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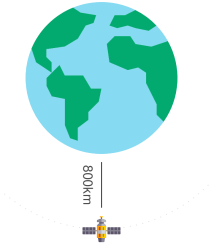

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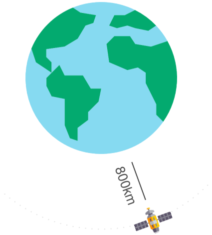
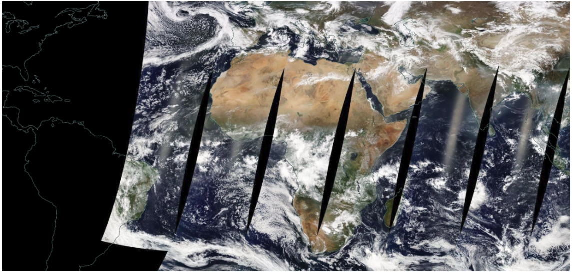


Global Environmental Satellites

Moderate Resolution Spectrometer

- images every day
- resolution $\approx 1 km$
- $>$ 50 spectral bands



`https://worldview.earthdata.nasa.gov/`

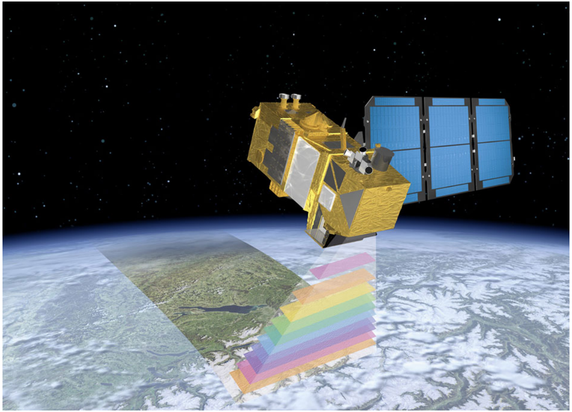
Multi Spectral Satellites – Example Sentinel 2 or Landsat

USGS Landsat

- spatial resolution 30m
- covers every point on Earth every 16 days
- 11 spectral bands
- since the 80s

ESA Sentinel-2

- spatial resolution 10m-60m
- covers every point on Earth every 2-5 days
- 13 spectral bands
- since 2016

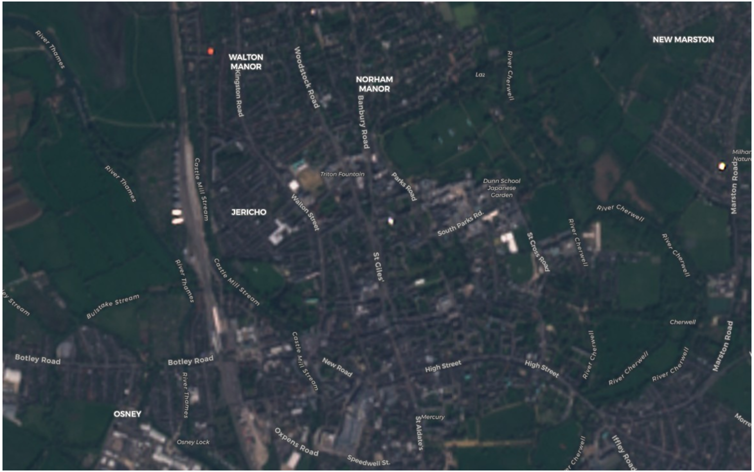


Multi Spectral Satellites – Example Sentinel 2

True Color

$$\boldsymbol{X} = \begin{pmatrix} \rho_{B1} \\ \rho_{B2} \\ \rho_{B3} \\ \rho_{B4} \\ \rho_{B5} \\ \rho_{B6} \\ \rho_{B7} \\ \rho_{B8} \\ \rho_{B8A} \\ \rho_{B9} \\ \rho_{B10} \\ \rho_{B11} \\ \rho_{B12} \end{pmatrix} \xrightarrow{\text{visualize}} \begin{pmatrix} \rho_{B4} \\ \rho_{B3} \\ \rho_{B2} \end{pmatrix}$$

`https://apps.sentinel-hub.com`



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$$\boldsymbol{X} = \begin{pmatrix} \rho_{B1} \\ \rho_{B2} \\ \rho_{B3} \\ \rho_{B4} \\ \rho_{B5} \\ \rho_{B6} \\ \rho_{B7} \\ \rho_{B8} \\ \rho_{B8A} \\ \rho_{B9} \\ \rho_{B10} \\ \rho_{B11} \\ \rho_{B12} \end{pmatrix} \xrightarrow{\textit{visualize}} \begin{pmatrix} \rho_{B8} \\ \rho_{B4} \\ \rho_{B3} \end{pmatrix}$$

https://apps.sentinel-hub.com

Multi Spectral Satellites – Example Sentinel 2

False Color Urban

$$\boldsymbol{X} = \begin{pmatrix} \rho_{B1} \\ \rho_{B2} \\ \rho_{B3} \\ \rho_{B4} \\ \rho_{B5} \\ \rho_{B6} \\ \rho_{B7} \\ \rho_{B8} \\ \rho_{B8A} \\ \rho_{B9} \\ \rho_{B10} \\ \rho_{B11} \\ \rho_{B12} \end{pmatrix} \xrightarrow{\text{visualize}} \begin{pmatrix} \rho_{B12} \\ \rho_{B11} \\ \rho_{B4} \end{pmatrix}$$

https://apps.sentinel-hub.com

Multi Spectral Satellites – Example Sentinel 2

Short-Wave Infra Red Bands

$$\boldsymbol{X} = \begin{pmatrix} \rho_{B1} \\ \rho_{B2} \\ \rho_{B3} \\ \color{orange}{\rho_{B4}} \\ \rho_{B5} \\ \rho_{B6} \\ \rho_{B7} \\ \rho_{B8} \\ \color{orange}{\rho_{B8A}} \\ \rho_{B9} \\ \rho_{B10} \\ \rho_{B11} \\ \color{orange}{\rho_{B12}} \end{pmatrix} \xrightarrow{\text{visualize}} \begin{pmatrix} \rho_{B12} \\ \rho_{B8A} \\ \rho_{B4} \end{pmatrix}$$

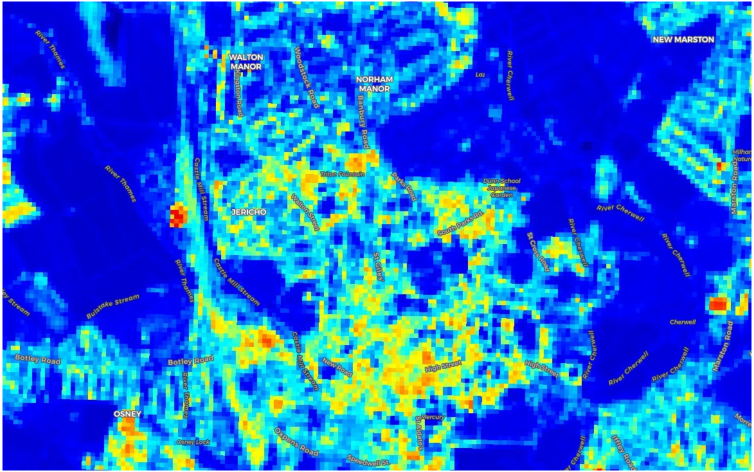
https://apps.sentinel-hub.com

Multi Spectral Satellites – Example Sentinel 2

MoistureIndex

$$
\boldsymbol{X} = \begin{pmatrix} \rho_{B1} \\ \rho_{B2} \\ \rho_{B3} \\ \rho_{B4} \\ \rho_{B5} \\ \rho_{B6} \\ \rho_{B7} \\ \rho_{B8} \\ \color{orange}{\rho_{B8A}} \\ \rho_{B9} \\ \rho_{B10} \\ \color{orange}{\rho_{B11}} \\ \rho_{B12} \end{pmatrix} \xrightarrow{\textit{visualize}} \left(\frac{\rho_{B8A} - \rho_{B11}}{\rho_{B8A} + \rho_{B11}} \right)
$$

`https://apps.sentinel-hub.com`

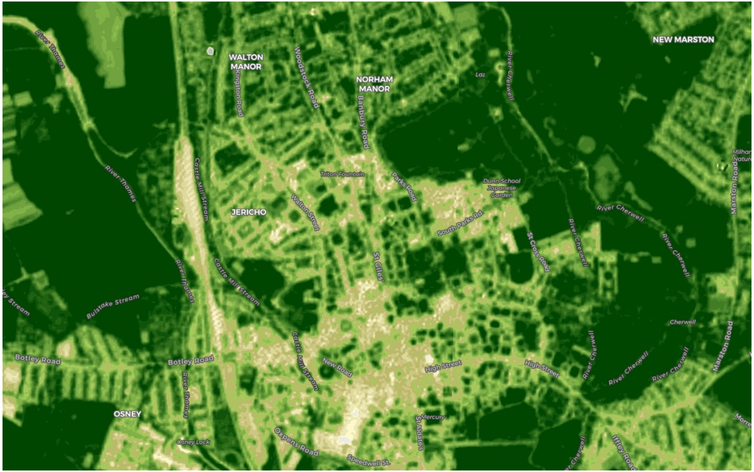


Multi Spectral Satellites – Example Sentinel 2

Vegetation Index (NDVI)

$$\boldsymbol{X} = \begin{pmatrix} \rho_{B1} \\ \rho_{B2} \\ \rho_{B3} \\ \rho_{B4} \\ \rho_{B5} \\ \rho_{B6} \\ \rho_{B7} \\ \rho_{B8} \\ \rho_{B8A} \\ \rho_{B9} \\ \rho_{B10} \\ \rho_{B11} \\ \rho_{B12} \end{pmatrix} \xrightarrow{\text{visualize}} \left(\frac{\rho_{B8} - \rho_{B4}}{\rho_{B8} + \rho_{B4}} \right)$$

`https://apps.sentinel-hub.com`



Multi Spectral Satellites – Example Sentinel 2

Water Index (NDWI)

$$\boldsymbol{X} = \begin{pmatrix} \rho_{B1} \\ \rho_{B2} \\ \rho_{B3} \\ \rho_{B4} \\ \rho_{B5} \\ \rho_{B6} \\ \rho_{B7} \\ \rho_{B8} \\ \rho_{B8A} \\ \rho_{B9} \\ \rho_{B10} \\ \rho_{B11} \\ \rho_{B12} \end{pmatrix} \xrightarrow{\text{visualize}} \left(\frac{\rho_{B3} - \rho_{B8}}{\rho_{B3} + \rho_{B8}} \right)$$

`https://apps.sentinel-hub.com`

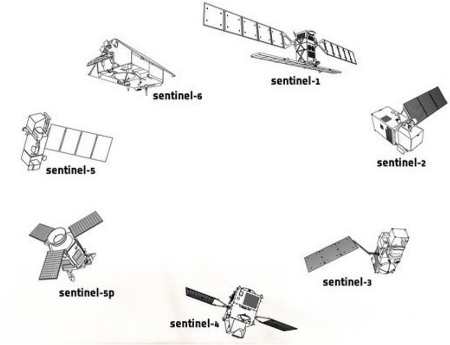
Takeaway: Each pixel has rich physical information

Open Data Policy!

This data is acquired globally
at regular time intervals
and is completely free to the public

Landsat
USGS
science for a changing world

MODIS
Moderate Resolution Imaging Spectroradiometer



https://wdc.dlr.de/sensors/modis/
https://www.usgs.gov/land-resources/nli/landsat
http://www.esa.int/spaceinimages/Images/2014/04/Sentinel_family

High (spatial) Resolution Satellites

Highest spatial detail ($< 1m$ spatial resolution).

Images acquired on an acquisition schedule

$$\boldsymbol{X} = \begin{pmatrix} \rho_{\text{red}} \\ \rho_{\text{green}} \\ \rho_{\text{blue}} \\ \rho_{\text{near-infrared}} \end{pmatrix}$$

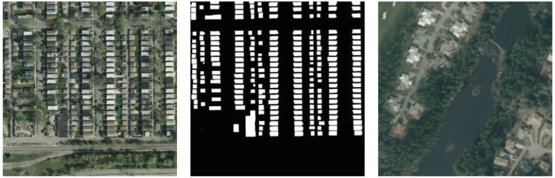
Computer Vision and High Resolution Data

SpaceNet Challenge
`https://spacenetchallenge.github.io/`

Inria Aerial Labelling Dataset
`https://project.inria.fr/aerialimagelabeling/`

SpaceNet®

Inria Aerial Image Labeling Dataset



Chicago | Chicago – reference | Kitsap County, WA

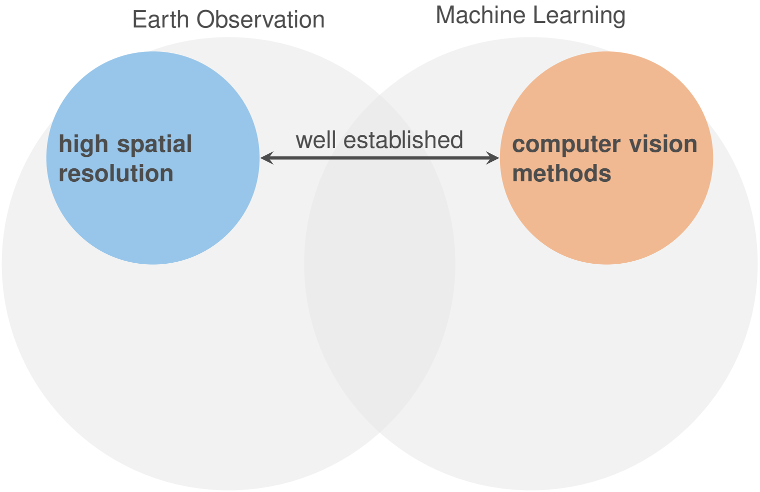
Kitsap County, WA – Reference | Vienna | Vienna – Reference

Takeaway: EO data has potential

Takeaway: only VHR has exposure in ML

Part II: Projects and Research

Multi-temporal Earth observation



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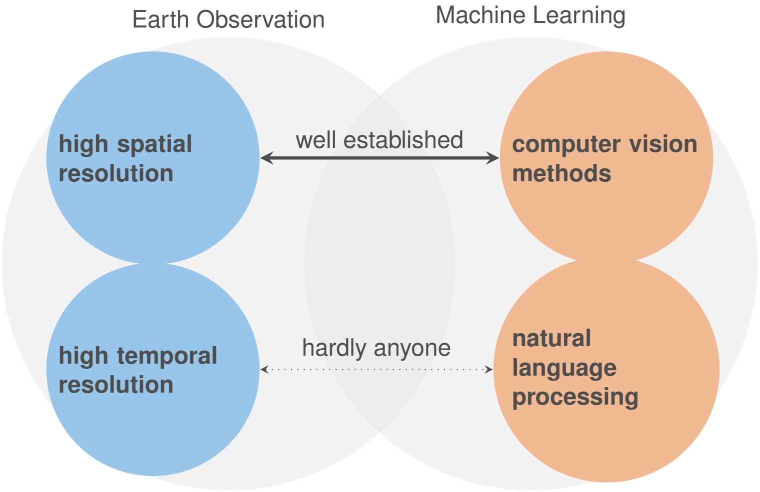

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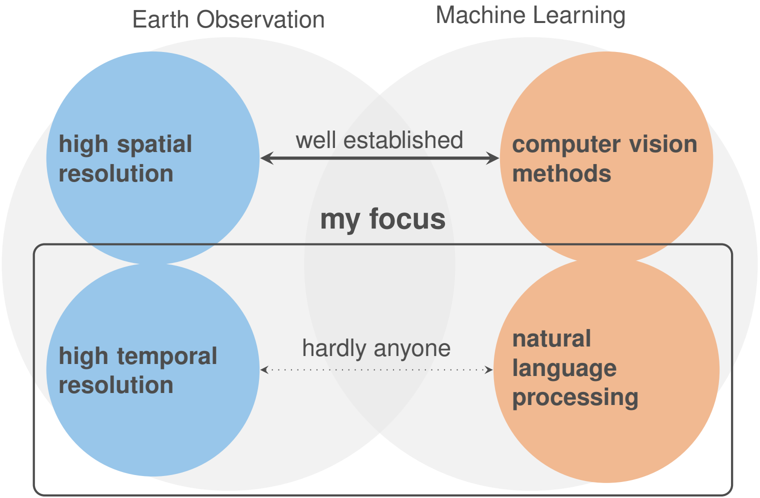
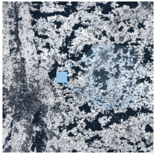
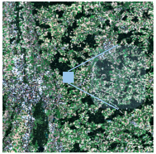
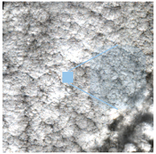
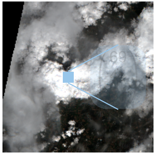


Example Analogy to Natural Language Processing

$\boldsymbol{x}_1$ $\boldsymbol{x}_2$ $\boldsymbol{x}_3$ $\boldsymbol{x}_4$

$\xrightarrow{\text{EO model}} f(\boldsymbol{X})$

$E(\textbf{The}) = \begin{pmatrix} 49 \\ 86 \\ 80 \end{pmatrix}$ $E(\textbf{eagle}) = \begin{pmatrix} 26 \\ 68 \\ 56 \end{pmatrix}$ $E(\textbf{has}) = \begin{pmatrix} 95 \\ 98 \\ 18 \end{pmatrix}$ $E(\textbf{landed}) = \begin{pmatrix} 44 \\ 87 \\ 99 \end{pmatrix}$ $\xrightarrow{\text{NLP model}} f(\boldsymbol{X})$

Structure

Vegetation Monitoring Learn a supervised classification model for Vegetation Classification

Early Time Series Classification Identify the class as early in the sequence as possible

Compiling Public Datasets bringing together the two communities by establishing datasets for multi-temporal Earth Observation data

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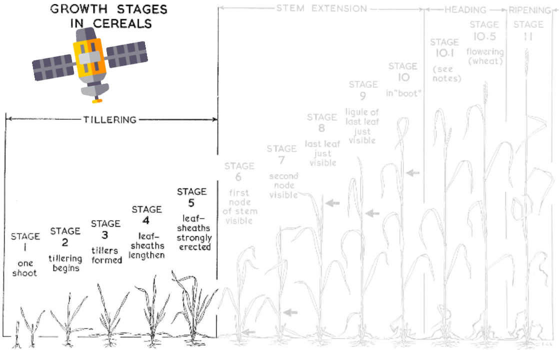
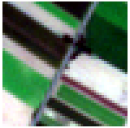
Vegetation Monitoring

Multi-temporal Vegetation Monitoring

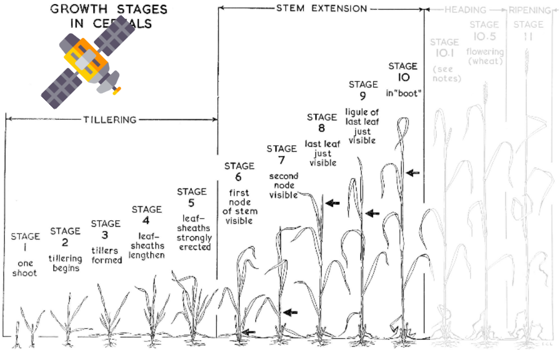


$$y = f_{\text{phenology}}(\boldsymbol{x}_t)$$

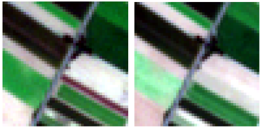


Large, E. C. (1954). Growth stages in cereals illustration of the Feekes scale. Plant pathology, 3(4), 128-129.

Multi-temporal Vegetation Monitoring

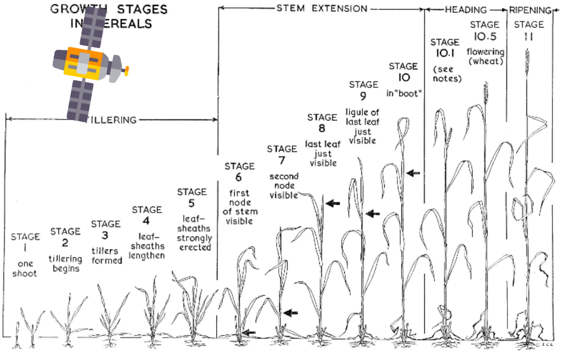


$$y = f_{\text{phenology}}(\boldsymbol{x}_t, \boldsymbol{x}_{t+1})$$

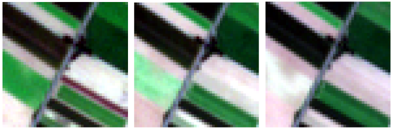


Large, E. C. (1954). Growth stages in cereals illustration of the Feekes scale. Plant pathology, 3(4), 128-129.

Multi-temporal Vegetation Monitoring

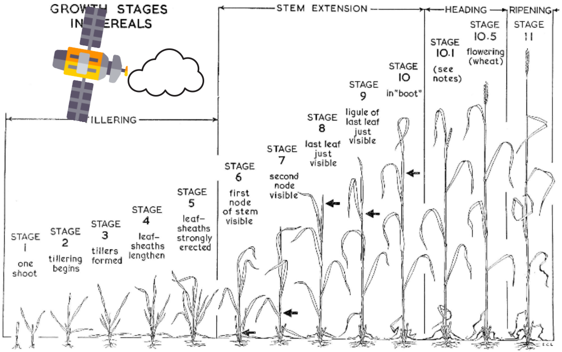


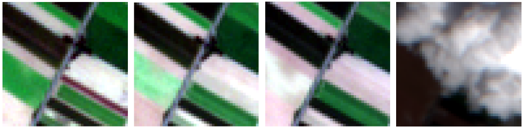
$$y = f_{\text{phenology}}(\boldsymbol{x}_t, \boldsymbol{x}_{t+1}, \boldsymbol{x}_{t+2})$$



Large, E. C. (1954). Growth stages in cereals illustration of the Feekes scale. Plant pathology, 3(4), 128-129.

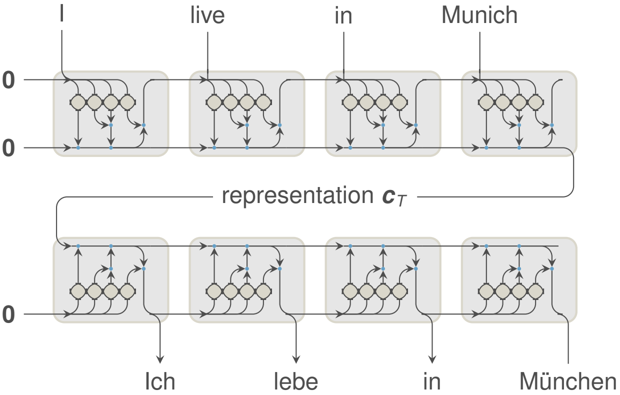
Multi-temporal Vegetation Monitoring





Large, E. C. (1954). Growth stages in cereals illustration of the Feekes scale. Plant pathology, 3(4), 128-129.

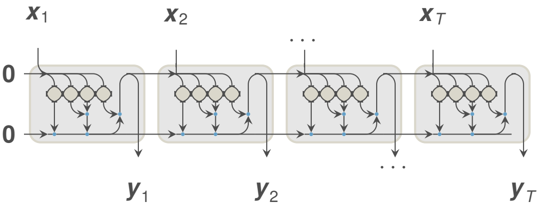
Looking at Sequence to Sequence Models from NLP

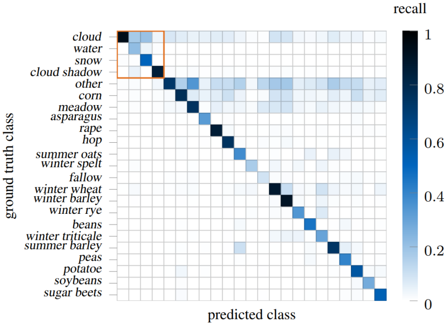


Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to sequence learning with neural networks. In Advances in neural information processing systems (pp. 3104-3112).

Temporal Vegetation Modelling with LSTMs

CVPR Earthvision 2017



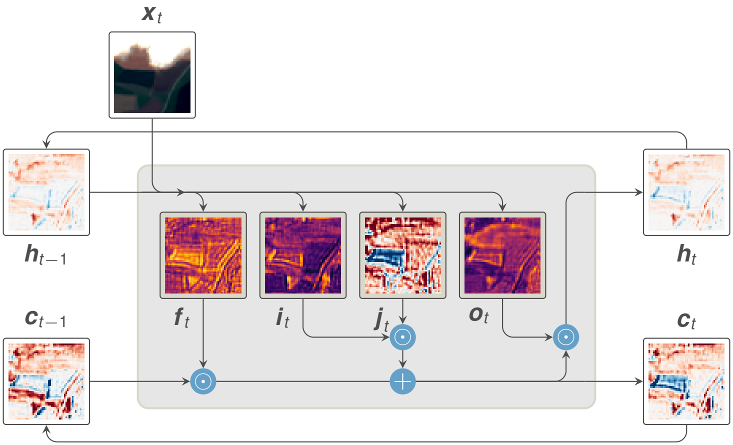


Rußwurm, M. and Körner, M. (2017). ***Temporal Vegetation Modelling using Long Short-Term Memory Networks for Crop Identification from Medium-Resolution Multi-Spectral Satellite Images****. In IEEE/ISPRS EarthVision 2017 Workshop, Proceedings of the IEEE CVPR Workshops.* ***Best Paper Award***

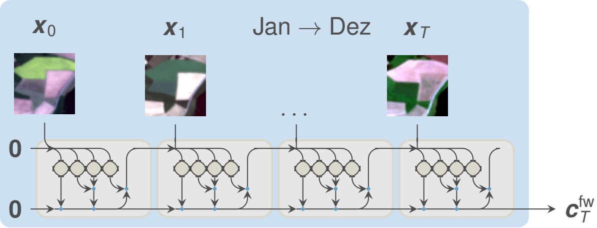
Recurrent Convolutional Neural Networks

Convolutional Long Short-Term Memory — ConvLSTM (Hochreiter & Schmidhuber, 1997)

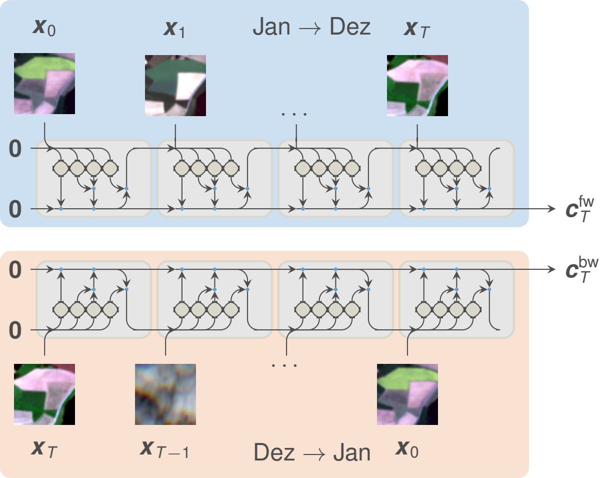
Convolutional LSTM: Xingjian, S. H. I., Chen, Z., Wang, H., Yeung, D. Y., Wong, W. K., & Woo, W. C. (2015). Convolutional LSTM network: A machine learning approach for precipitation nowcasting. In Advances in neural information processing systems (pp. 802-810).



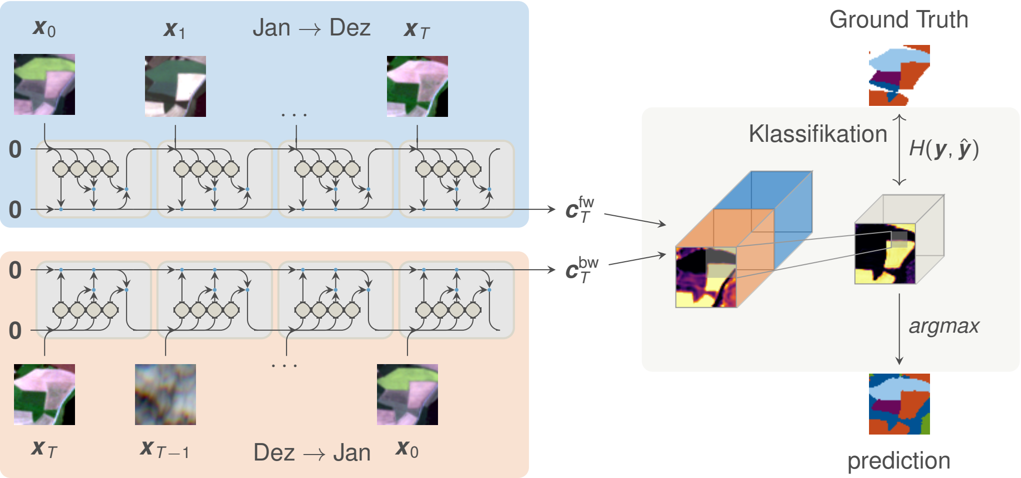
Classification ConvLSTM Network



Classification ConvLSTM Network

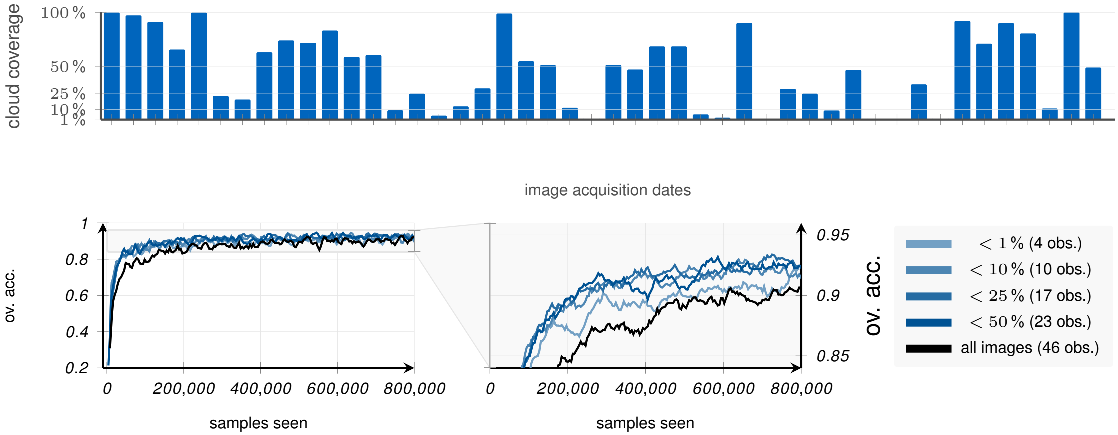


Classification ConvLSTM Network

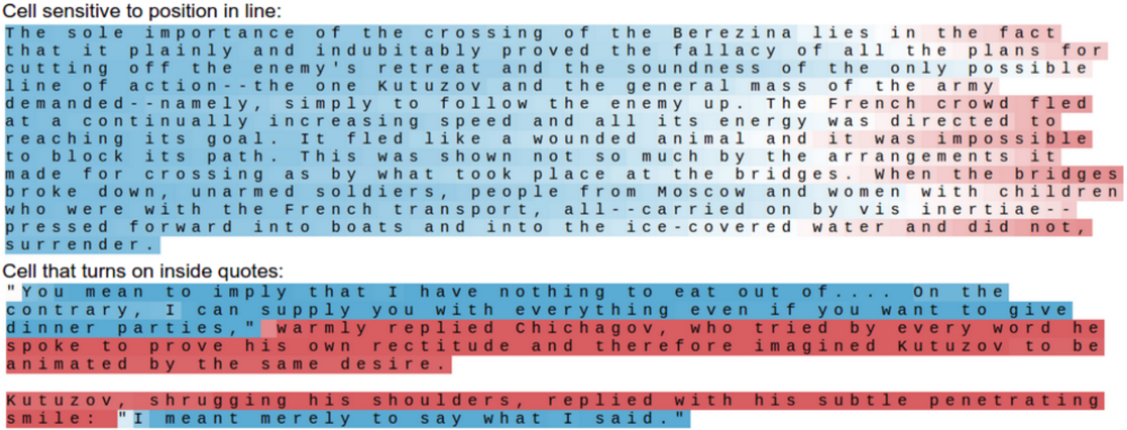


Surprise: It worked without specifically labeling clouds!

ConvLSTM robust to clouds



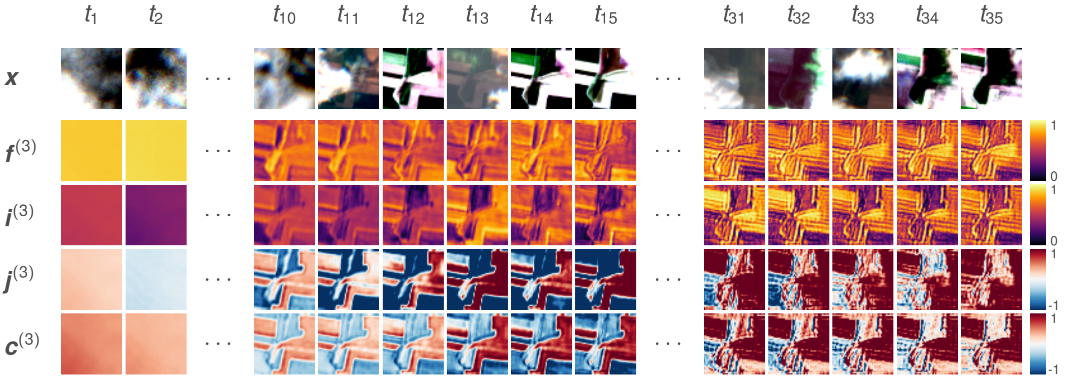
Remembering Karpathy's "Unreasonable Effectiveness of RNNs"



http://karpathy.github.io/2015/05/21/rnn-effectiveness/

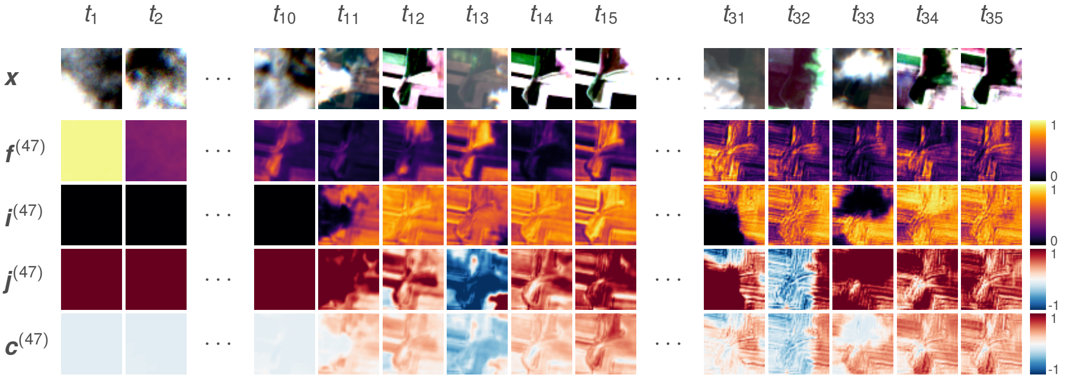
Internal States Encode increasingly Classification Features

LSTM cell **47** of 256



Found Cloud Masking Cells in the RNN

LSTM cell **47** of 256



Paper and Code

Github + DockerHub + Continuation with GAF AG

`https://github.com/TUM-LMF/MTLCC` `https://github.com/TUM-LMF/MTLCC-pytorch`

`http://www.lmf.bgu.tum.de/vision/`

*Rußwurm, M. and Körner, M. (2017). **Temporal Vegetation Modelling using Long Short-Term Memory Networks for Crop Identification from Medium-Resolution Multi-Spectral Satellite Images**. In IEEE/ISPRS EarthVision 2017 Workshop, Proceedings of the IEEE CVPR Workshops.*

*Rußwurm M., Körner M. (2018). **Multi-Temporal Land Cover Classification with Sequential Recurrent Encoders**. ISPRS International Journal of Geo-Information. https://arxiv.org/abs/1802.02080. (in review)*

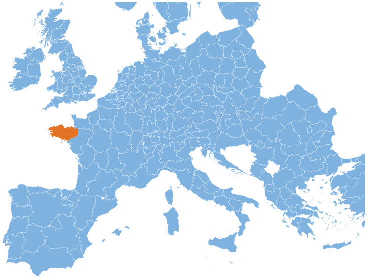
Early Time Series Classification

Winter Research Stay at IRISA Obelix Lab in France

Research Stay

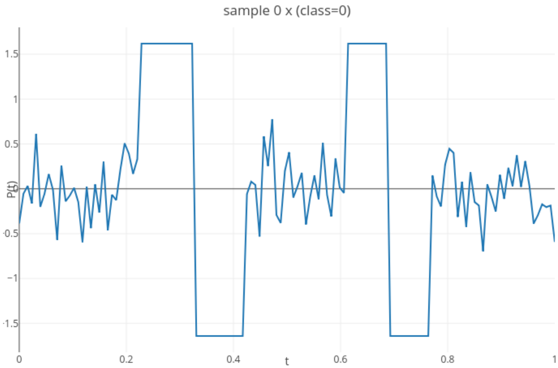
- Prof. **Sebastien Lefèvre** and Prof. **Romain Tavenard**
- Obelix: **Environment observation** with **complex imagery**
- Vannes and Rennes, Britanny, France

`http://www-obelix.irisa.fr/`

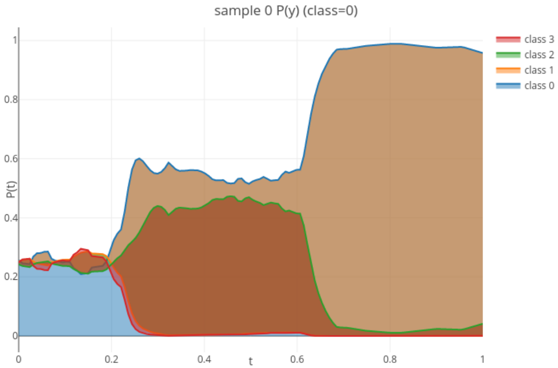


Class Predictions

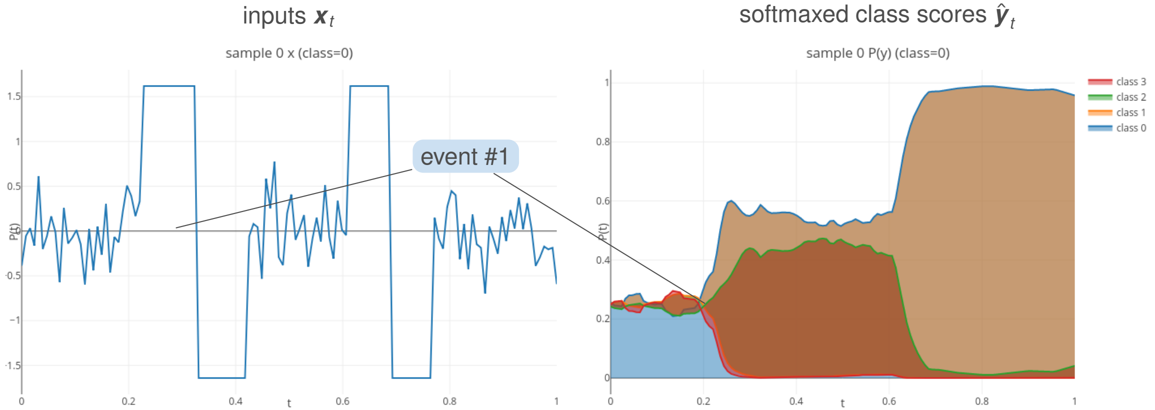
inputs $\boldsymbol{x}_t$



softmaxed class scores $\hat{\boldsymbol{y}}_t$



Class Predictions



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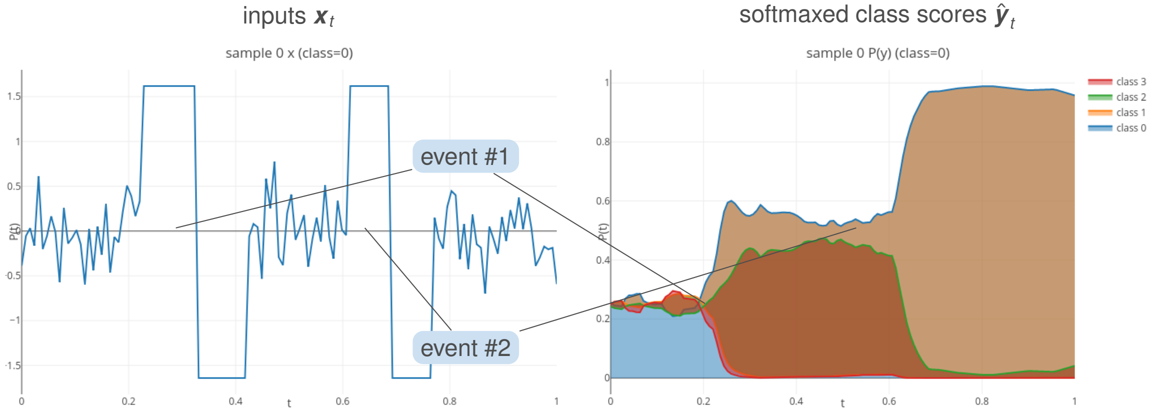
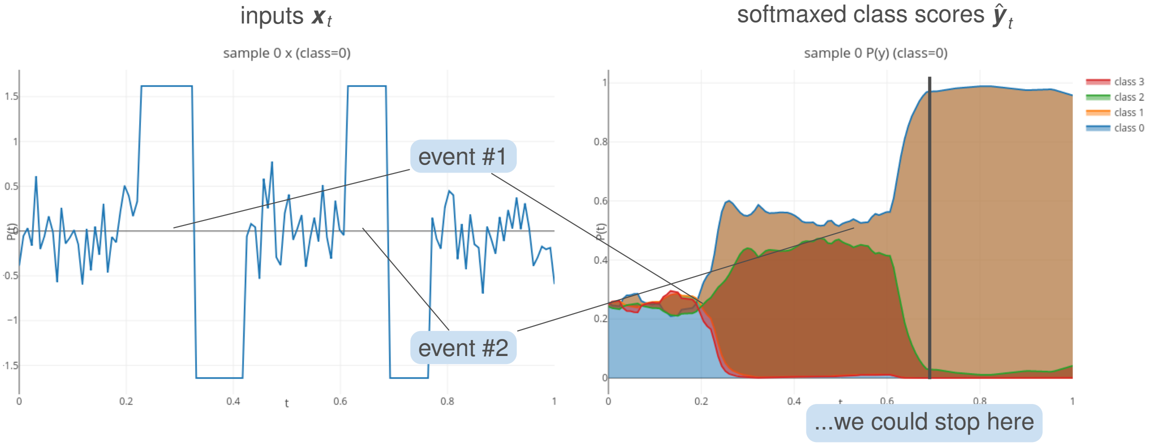
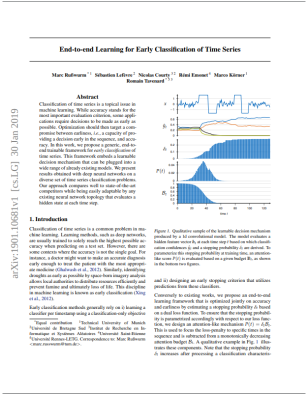


Class Predictions



ArXiv Paper: End-to-end Learning for Early Classification of Time Series

Rußwurm, M., Lefèvre, S., Courty, N., Emonet, R., Körner, M., & Tavenard, R. (2019). **End-to-end Learning for Early Classification of Time Series**. arXiv preprint arXiv:1901.10681.



arXiv:1901.10681v1 [cs.LG] 30 Jan 2019

End-to-end Learning for Early Classification of Time Series

Marc Rußwurm [*1] Sébastien Lefèvre [2] Nicolas Courty [3 2] Rémi Emonet [4] Marco Körner [1]
Romain Tavenard [*5 3]

Abstract

Classification of time series is a topical issue in machine learning. While accuracy stands for the most important evaluation criterion, some applications require decisions to be made as early as possible. Optimization should then target a compromise between earliness, *i.e.*, a capacity of providing a decision early in the sequence, and accuracy. In this work, we propose a generic, end-to-end trainable framework for *early classification* of time series. This framework embeds a learnable decision mechanism that can be plugged into a wide range of already existing models. We present results obtained with deep neural networks on a diverse set of time series classification problems. Our approach compares well to state-of-the-art competitors while being easily adaptable by any existing neural network topology that evaluates a hidden state at each time step.

1. Introduction

Classification of time series is a common problem in machine learning. Learning methods, such as deep networks, are usually trained to solely reach the highest possible accuracy when predicting on a test set. However, there are some contexts where the accuracy is not the single goal. For instance, a doctor might want to make an accurate diagnosis early enough to treat the patient with the most appropriate medicine (Ghalwash et al., 2012). Similarly, identifying droughts as early as possible by space-born imagery analysis allows local authorities to distribute resources efficiently and prevent famine and ultimately loss of life. This discipline in machine learning is known as early classification (Xing et al., 2012).

Early classification methods generally rely on i) learning a classifier per timestamp using a classification-only objective

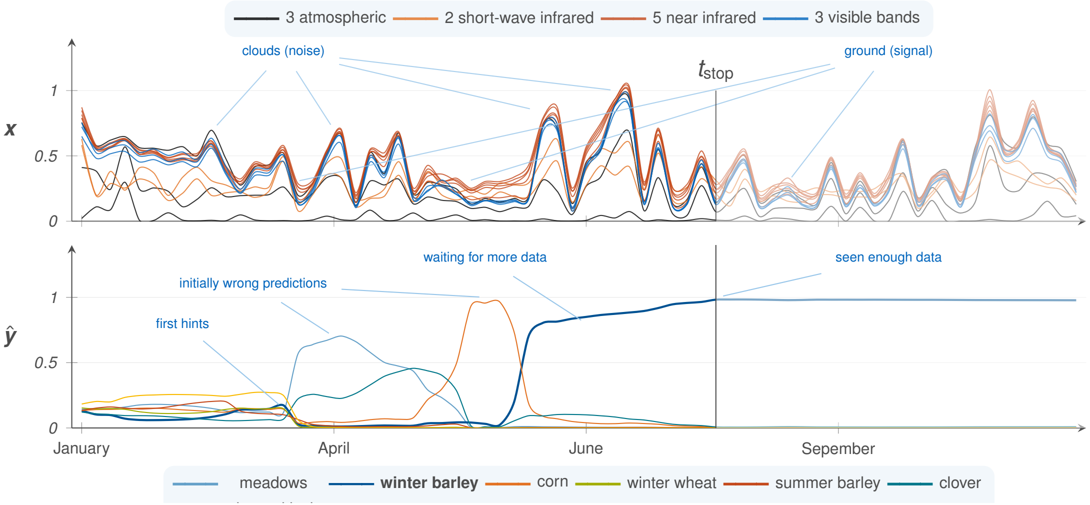
*Equal contribution [1]Technical University of Munich [2]Université de Bretagne Sud [3]Institut de Recherche en Informatique et Systèmes Aléatoires [4]Université Saint-Etienne [5]Université Rennes-LETG. Correspondence to: Marc Rußwurm <marc.russwurm@tum.de>.

Figure 1. Qualitative sample of the learnable decision mechanism produced by a 1d convolutional model. The model evaluates a hidden feature vector h_t at each time step t based on which classification confidences $\hat{y}_t$ and a stopping probability δ_t are derived. To parameterize this stopping probability at training time, an attention-like score $P(t)$ is evaluated based on a given budget $\mathbb{B}_t$, as shown in the bottom two figures.

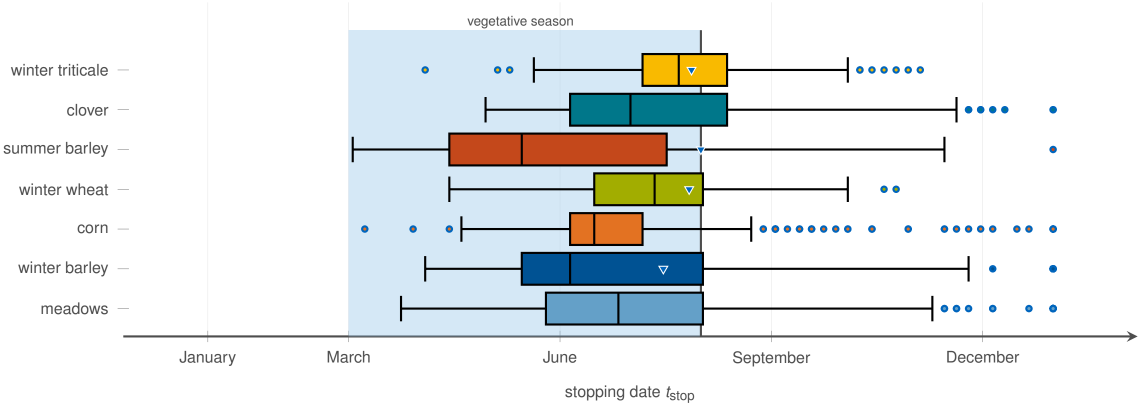
and ii) designing an early stopping criterion that utilizes predictions from these classifiers.

Conversely to existing works, we propose an end-to-end learning framework that is optimized jointly on accuracy and earliness by estimating a stopping probability δ_t based on a dual loss function. To ensure that the stopping probability is parametrized accordingly with respect to our loss function, we design an attention-like mechanism $P(t) = \delta_t \mathcal{B}_t$. This is used to focus the loss-penalty to specific times in the sequence and is subtracted from a monotonically decreasing attention budget $\mathcal{B}_t$. A qualitative example in Fig. 1 illustrates these components. Note that the stopping probability δ_t increases after processing a classification characteris-

Early Classification on Remote Sensing Data



Stopping times per crop Class



Impact of Early Classification on Vegetation Data

supervised end-to-end learning scenario

we get a stopping time **for free** solely from classifying labels

relate to **characteristic features**, i.e., **crop phenology**

next: assess seasonal shifts in **vegetation phenology** due to **environmental conditions**

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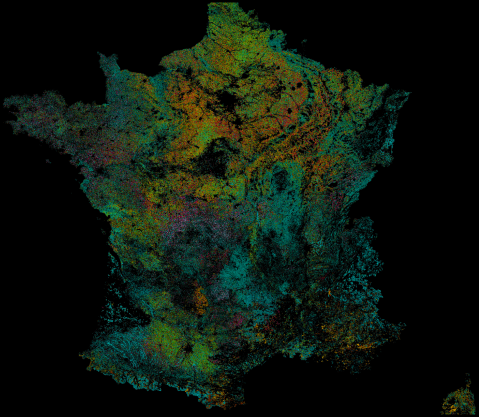
Compiling Datasets



Two Perspectives

Earth Observation

method is a **tool** for our **data**

should generalize to applications of a specific sub-field

data has specific **phyisical properties**

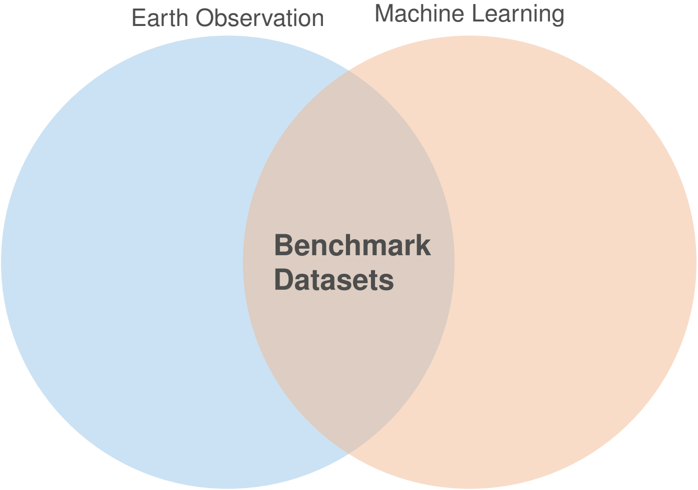
Machine Learning

data is a **benchmark** for our **method**

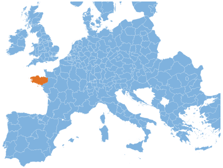
must generalize to many fields of applica-tions

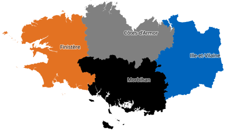
data is a **feature vector**

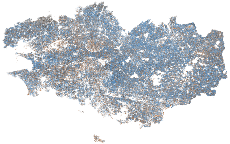
Common Datasets

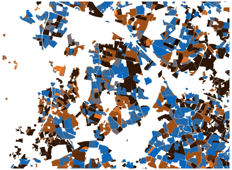


BreizhCrops Dataset (available by next week!)

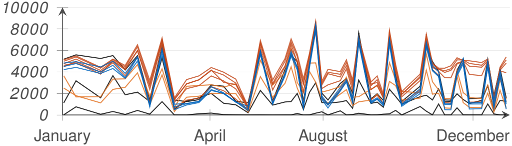




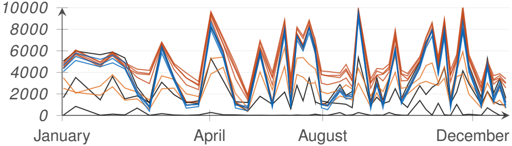




corn grain and silage



temporary meadows



580k samples of Time Series ***X*** and labels ***y***.

`https://github.com/TUM-LMF/BreizhCrops`

Challenges and Impact

Impact

- large scale **real-world dataset**
- effectively **unlimited data** (spatially and temporally)
- **assessing generalization** over large regions
- potential for further **vegetation characteristics** (drought indicator, early classification, crop yield)

Challenges and Impact

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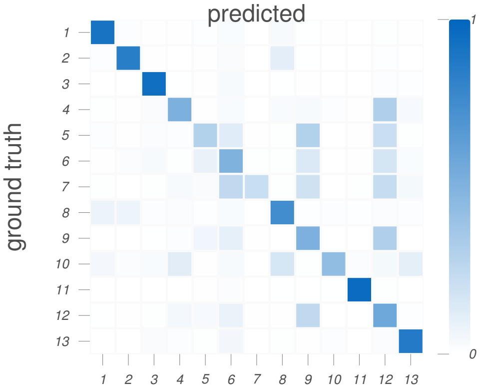
- **assessing generalization** over large regions
- potential for further **vegetation characteristics** (drought indicator, early classification, crop yield)

Challenges

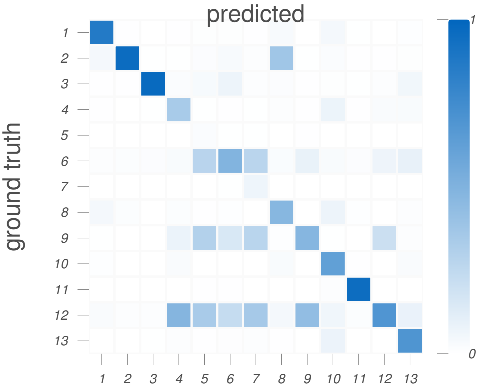
- **Imbalanced** class **labels**
- Classes with **similar characteristics**
- Non-Gaussian noise induced by **clouds**
- **Regional variations** in the class distributions
- **Spatial autocorrelation**
- **Irregular** temporal **sampling** distance
- **Variable sequence** length

Multi-Layer RNN baseline

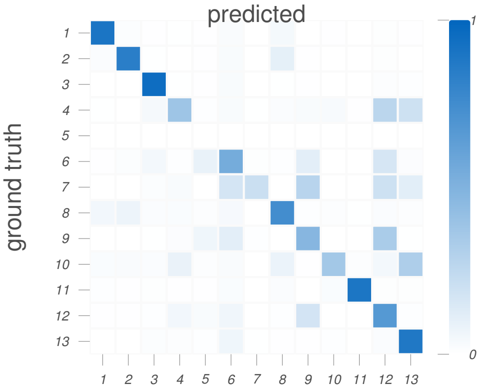
Precision

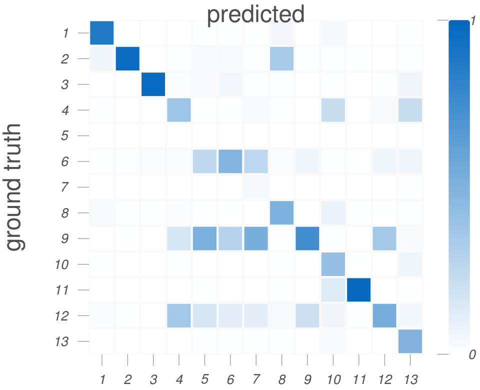


Recall

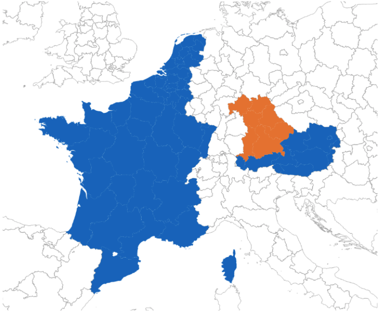


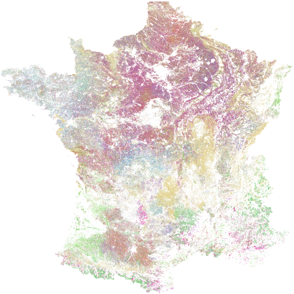
Transformer baseline

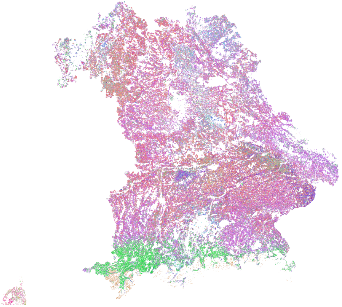




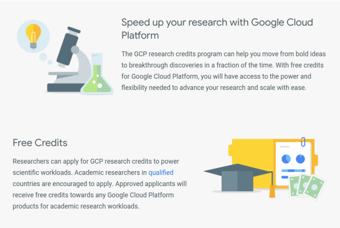
Going Big...







Supported by Google Research Credits



Google

Part III: Initiatives between EO and ML

Satellite Data Fusion for disaster response

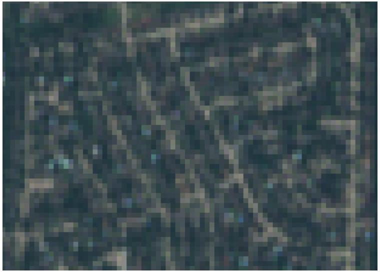
ARTIFICIAL INTELLIGENCE FOR SPACE EXPLORATION AND ALL HUMANKIND

Detection of Flooded Buildings with Multi-Sensor Data Fusion

0.5m post-disaster

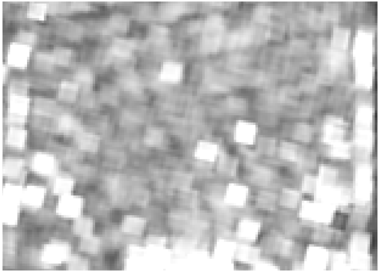
very high resolution

10m pre-disaster



optical

10m pre-disaster



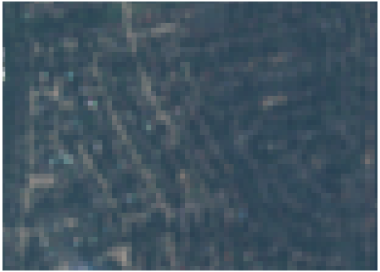
radar

Detection of Flooded Buildings with Multi-Sensor Data Fusion

0.5m post-disaster

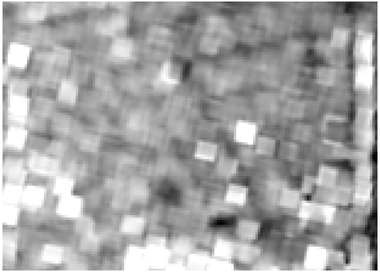
very high resolution

10m post-disaster



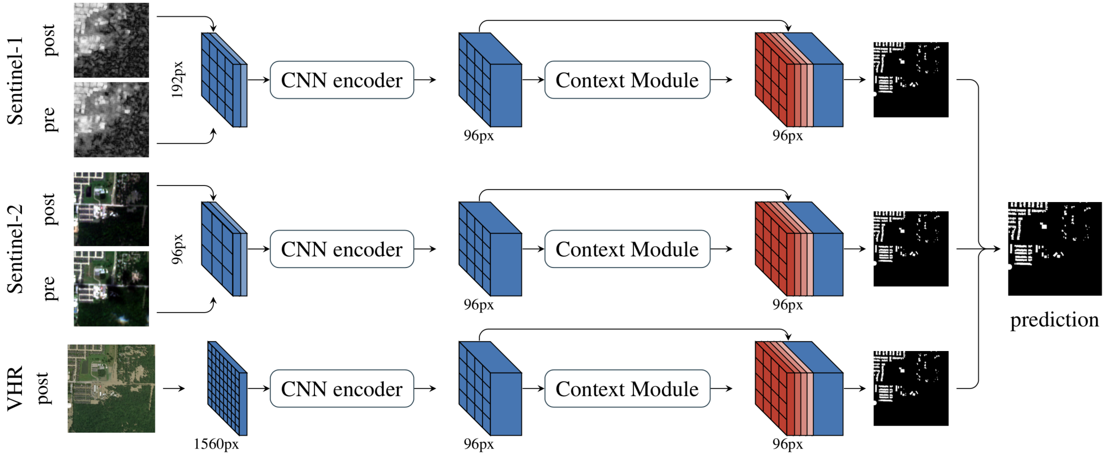
optical

10m post-disaster



radar

Multi^{3}Net



Sentinel-1
post
pre
192px
CNN encoder
96px
Context Module
96px
Sentinel-2
post
pre
96px
CNN encoder
96px
Context Module
96px
VHR
post
1560px
CNN encoder
96px
Context Module
96px
prediction

Publications and Code

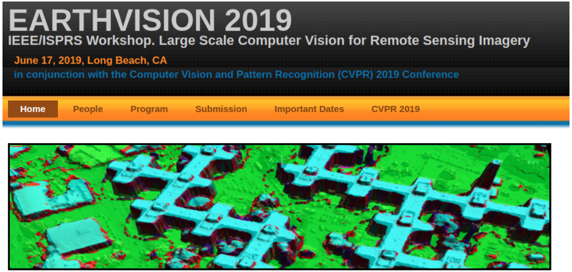
AAAI 2019 Conference Paper:
Rudner, T. G., Rußwurm, M., Fil, J., Pelich, R., Bischke, B., Kopackova, V., & Bilinski, P. (2019). Multi ^{3} Net: Segmenting Flooded Buildings via Fusion of Multiresolution, Multisensor, and Multitemporal Satellite Imagery. Association for the Advancement of Artificial Intelligence AAAI-19.

2 NeurIPS Workshop Papers at **AI for Social Good** and **Spatio-Temporal Workshops**.

GitHub `https://github.com/FrontierDevelopmentLab/multi3net`

Workshops

CVPR EarthVision



Workshop CVPR **June 17, 2019**

`https://www.grss-ieee.org/earthvision2019/`

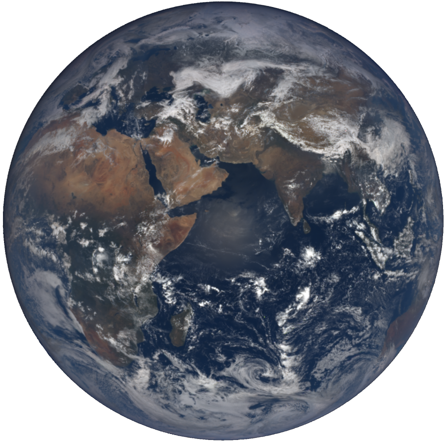
ECML MACLEAN

Deadline **Deadline June 10th, 2019**
Workshop ECML **September 20th, 2019**

Summary

Earth Observation

- general overview on optical data
- complexity of Earth Observation data
- showed the balance between **spatial**, **temporal** and **spectral** resolution



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- general overview on optical data
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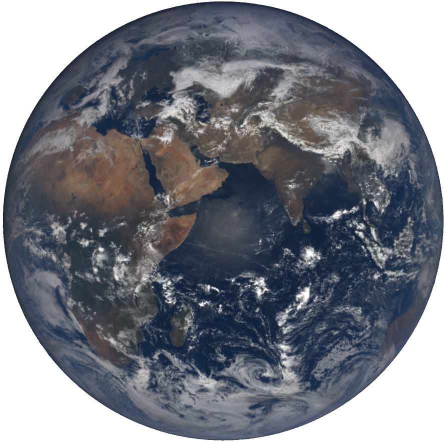
Projects

- illustrated some ML-related tasks
- translate methods between disciplines
- connect via huge Benchmark Datasets



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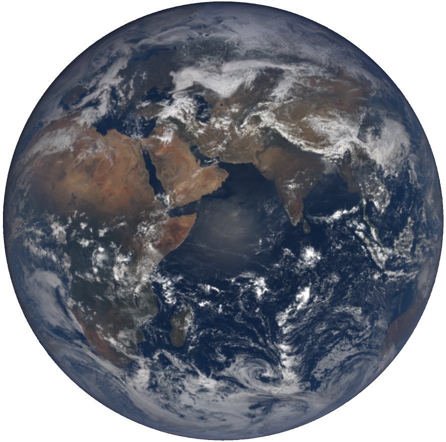
Initiatives

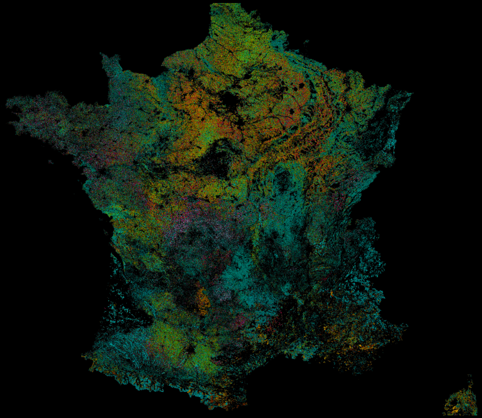
- hope to **see you at one of the Workshops**
- or at **Frontier Developments Lab**!



Thank you!

Twitter: @marccoru — **Github**: @marccoru or @tum-lmf — **Chair** `lmf.bgu.tum.de/vision`

BreizhCrops `https://github.com/TUM-LMF/BreizhCrops`



Questions/Input?

Twitter: @marccoru — **Github**: @marccoru or @tum-lmf — **Chair** `lmf.bgu.tum.de/vision`

BreizhCrops `https://github.com/TUM-LMF/BreizhCrops`

Thank you!

Papers:

Rußwurm, M. and Körner, M. (2017). **Temporal Vegetation Modelling using Long Short-Term Memory Networks for Crop Identification from Medium-Resolution Multi-Spectral Satellite Images**. In IEEE/ISPRS EarthVision 2017 Workshop, Proceedings of the IEEE CVPR Workshops. **Best Paper Award**

Rußwurm, M., Lefèvre, S., Courty, N., Emonet, R., Körner, M., & Tavenard, R. (2019). **End-to-end Learning for Early Classification of Time Series**. arXiv preprint arXiv:1901.10681.

Rußwurm, M., & Körner, M. (2018). **Multi-temporal land cover classification with sequential recurrent encoders**. ISPRS International Journal of Geo-Information, 7(4), 129.

Rußwurm, M., & Körner, M. (2018). **Convolutional LSTMs for Cloud-Robust Segmentation of Remote Sensing Imagery**. NeurIPS2018 Spatiotemporal Workshop. https://openreview.net/pdf?id=Sye7df9CK7

Rudner, T. G. J.; Rußwurm, M.; Fil, J.; Pelich, R.; Bischke, B.; Kopačková, V.; Biliński, P. (2019) **Segmenting Flooded Buildings via Fusion of Multiresolution, Multisensor, and Multitemporal Satellite Imagery**. In AAAI.

Twitter

https://twitter.com/MarcCoru

Github

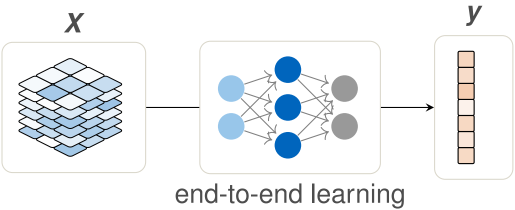
https://github.com/marccoru

https://github.com/TUM-LMF

Our Agenda

use pure **data-driven end-to-end** learning

- no pre/postprocessing of data
- top-of-atmosphere data
- no atmospheric correction
- no cloud filtering
- no additional image registration



adapt established methods to EO Sensors

- NLP to EO: Sentence translation to image sequence classification

UCR Datasets

broad family of **46 diverse datasets**

accuracies reported from other early classification approaches

covers **sensor data**, **motion tracking**, **electrocardiography data**

many, but **small datasets** (overall circa 500 MB)

http://www.timeseriesclassification.com/

Communications

Earth Observation

method is a **tool** for our **data**

should generalize to applications of a specific sub-field

data has specific **phyisical properties**

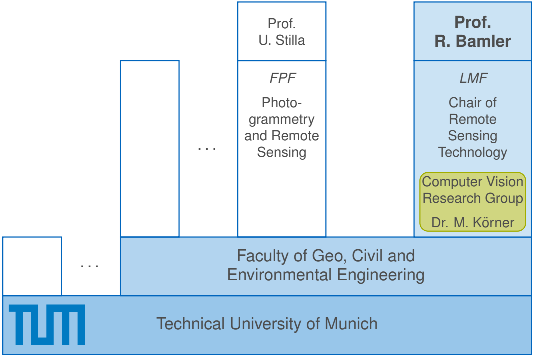
Machine Learning

data is a **benchmark** for our **method**

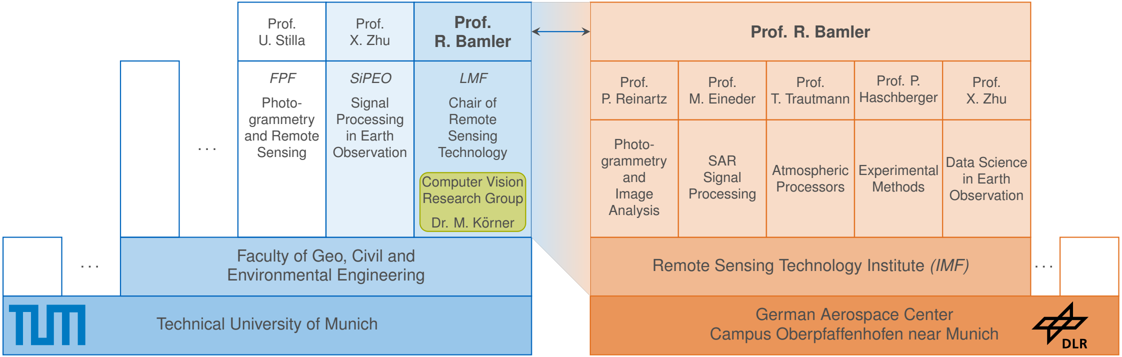
must generalize to many fields of applica-tions

data is a **feature vector**

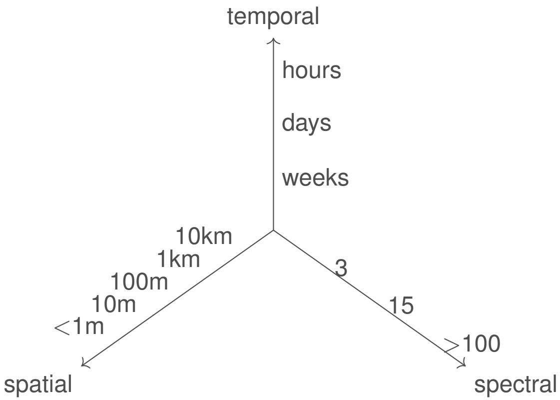
Chair of Remote Sensing Technology



Chair of Remote Sensing Technology



Summary: Balancing Resolutions



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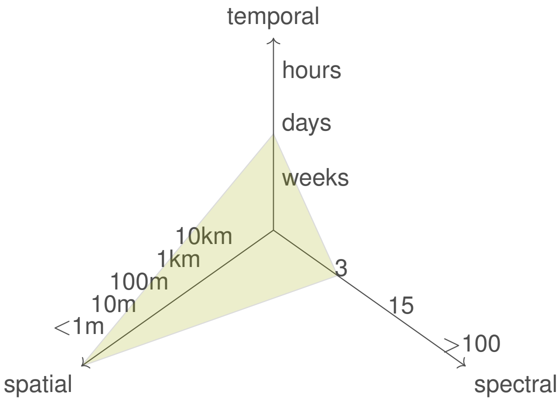
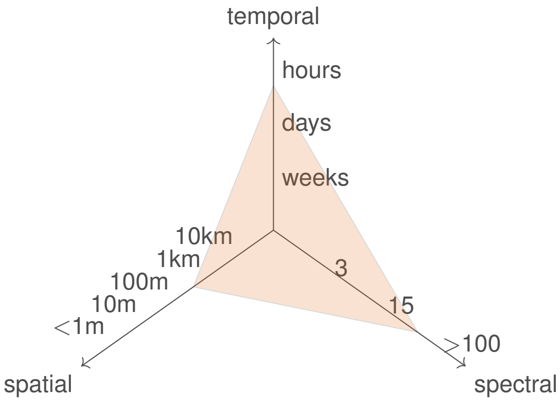


Scheduled Acquisitions

very high spatial Resolution Imagery

Summary: Balancing Resolutions



Scheduled Acquisitions

very high spatial Resolution Imagery

Global coverage and open data policy

multi-spectral satellites

environmental satellites

weather satellites

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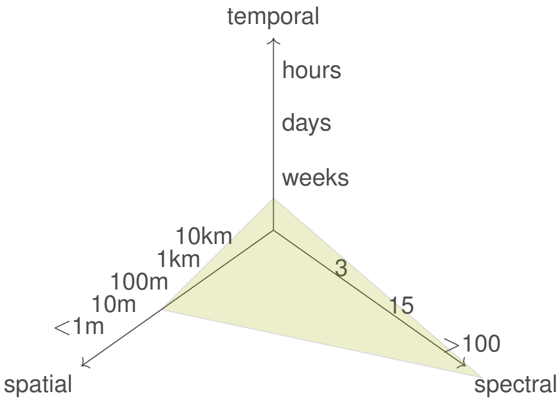

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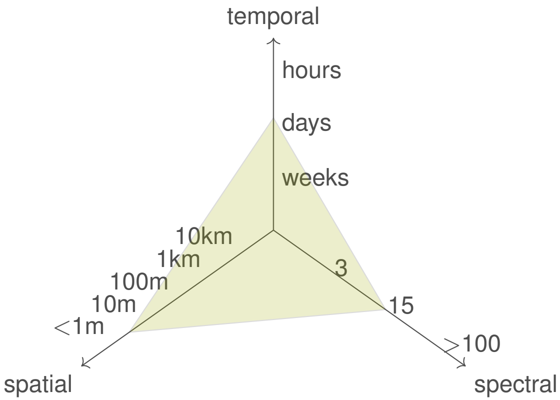

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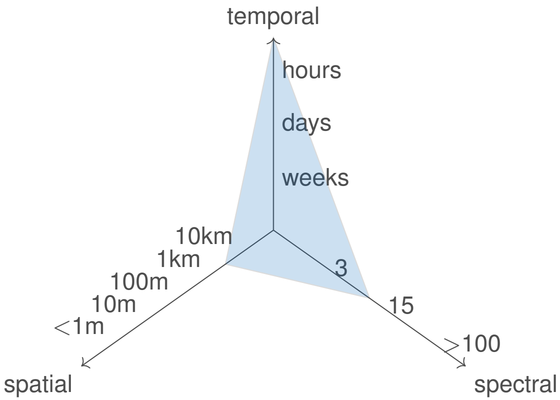

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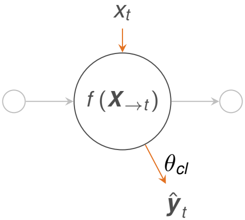
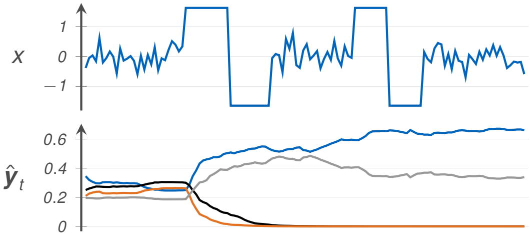
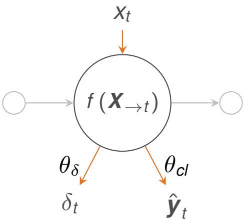
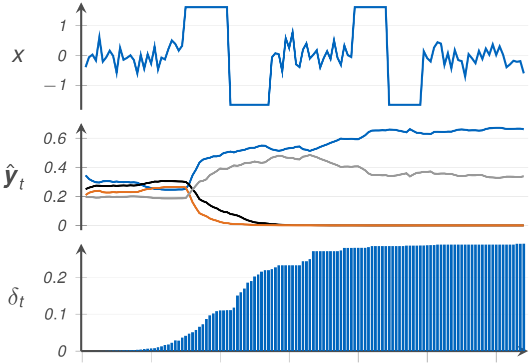
Augmenting Classification Models





Augmenting Classification Models





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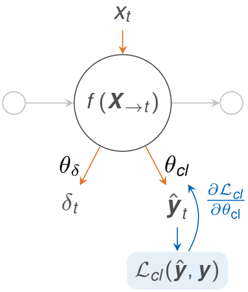

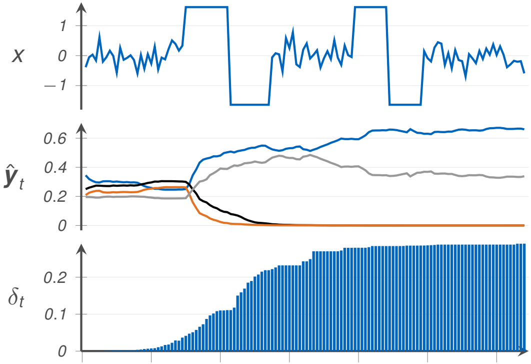

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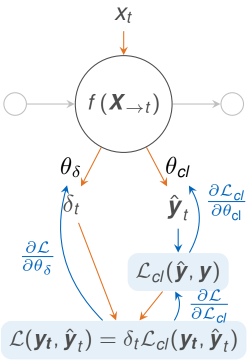

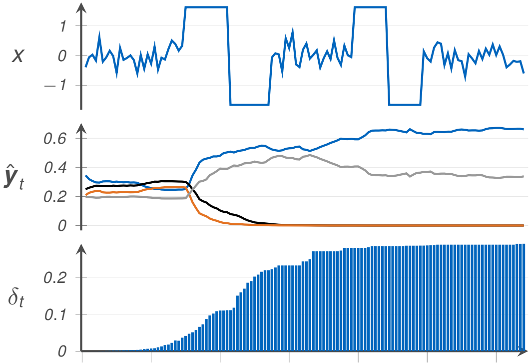

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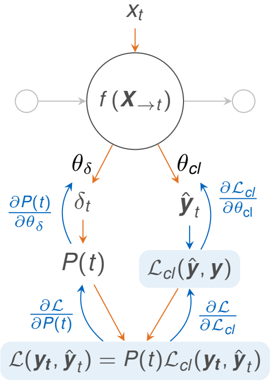
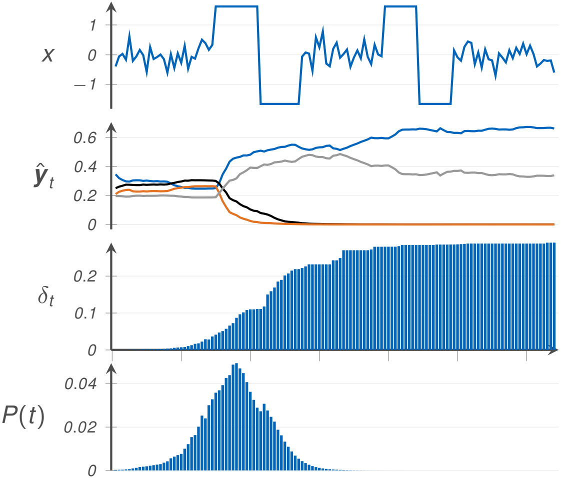
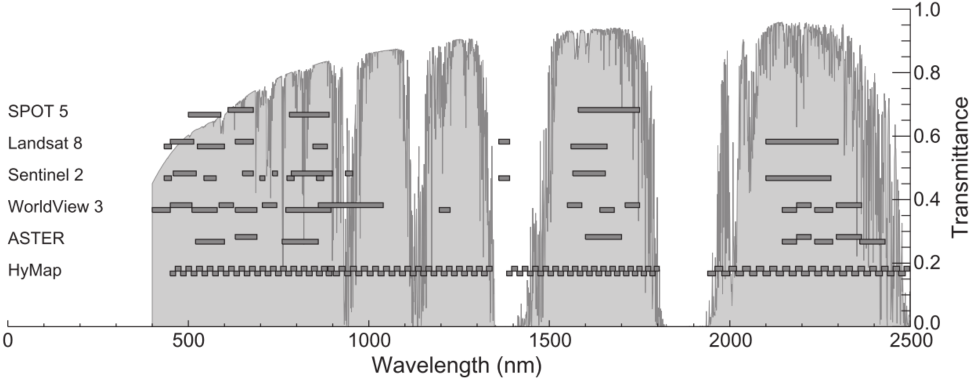




Earliness-Aware Loss function

$$\mathcal{L} = P(t)\left(\alpha(1 - \hat{\boldsymbol{y}}^{+}) + (1 - \alpha)\,\frac{t}{T}\right)$$

Spectral Bands



Van der Meer, F. D., Van der Werff, H. M. A., & Van Ruitenbeek, F. J. A. (2014). Potential of ESA's Sentinel-2 for geological applications. Remote sensing of environment, 148, 124-133.

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GunPoint dataset

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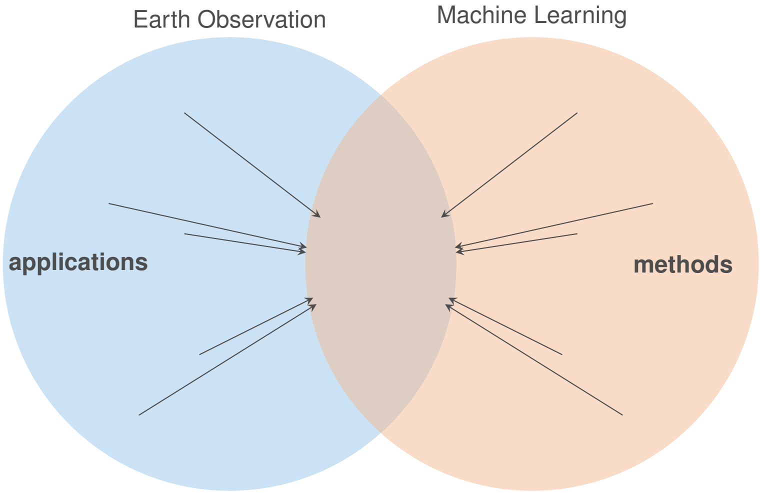
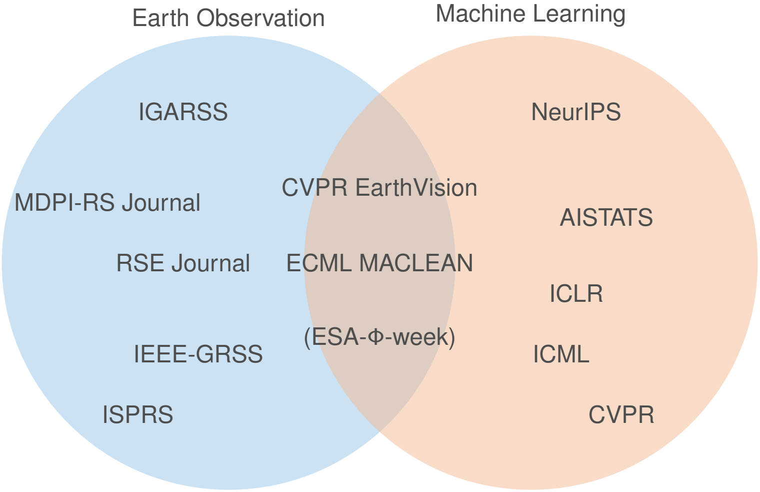
Two Fields


Earth Observation
Machine Learning
applications
methods

Communities



MODIS Satellite

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