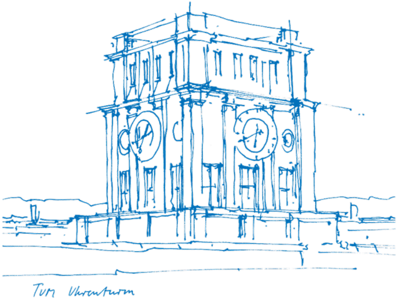
Remote Sensing Technology
TUM Department of Civil, Geo and Environmental Engineering
Technical University of Munich

Learning Vegetation Models from Satellite Data

Institut national de l'information géographique et forestière (IGN)

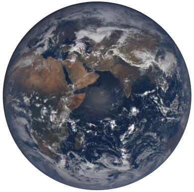
Marc Rußwurm, advised by Dr. rer. nat. Marco Körner

July 10th 2019, Paris



Background

Earth Observation



2012-2018
Bachelor/Master
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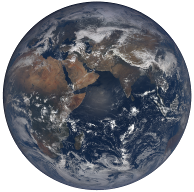

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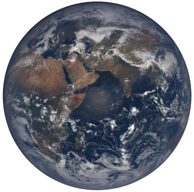

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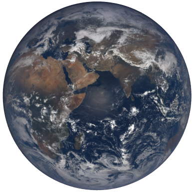

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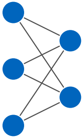
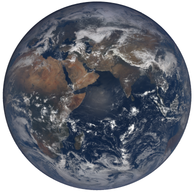
Machine Learning



Background

Earth Observation



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Disaster Relief with **CNN data fusion**

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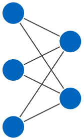

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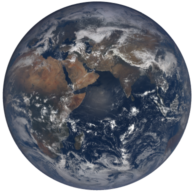

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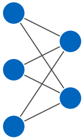

Structure

Vegetation Monitoring via a supervised classification model for crop type mapping

Early Time Series Classification to identify a class as early in the sequence as possible

Compiling Datasets engaging the machine learning community with (multi-temporal) remote sensing data.

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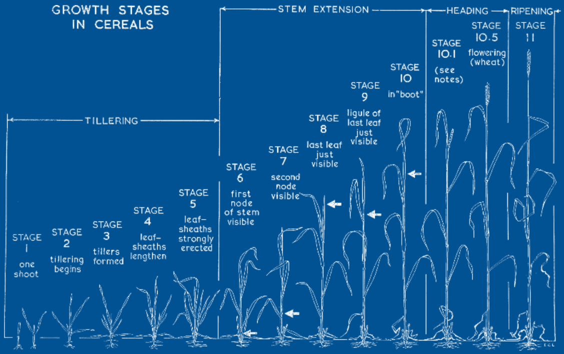
Vegetation Modeling



(Large et al., 1954)

Photosynthesis

$$6CO_2 \;+\; 6H_2O \;\rightarrow\; C_6H_{12}O_6 \;+\; 6O_2$$

Photosynthesis

$$6CO_2 + 6H_2O \rightarrow C_6H_{12}O_6 + 6O_2$$

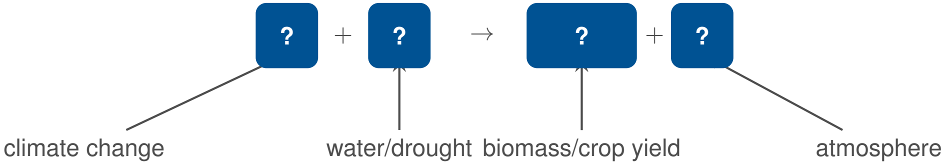
climate change

water/drought

biomass/crop yield

atmosphere

Photosynthesis



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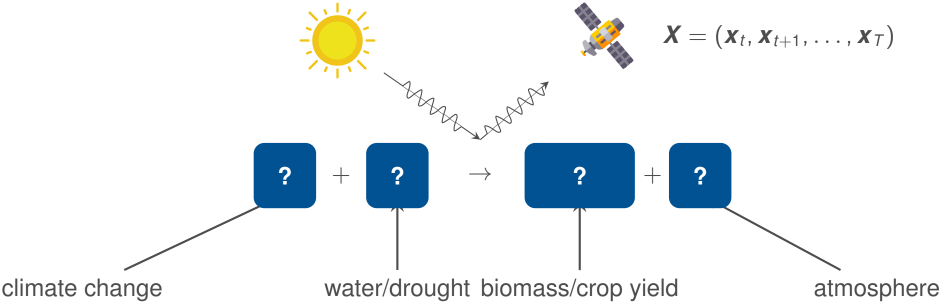

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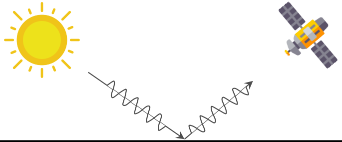
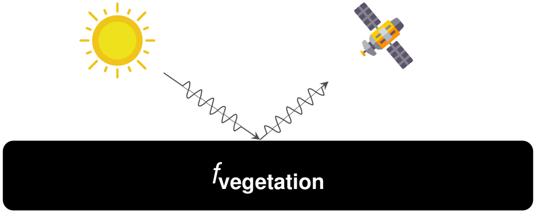


$$\boldsymbol{X} = (\boldsymbol{x}_t, \boldsymbol{x}_{t+1}, \dots, \boldsymbol{x}_T)$$

$f_{\textbf{vegetation}}$

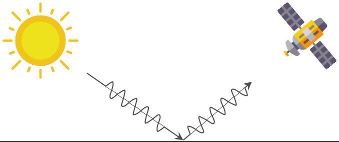
Photosynthesis



$$(\boldsymbol{x}_t, \boldsymbol{x}_{t+1}, \ldots, \boldsymbol{x}_T)$$

Problem: un/self-supervised learning of a vegetation model **is difficult**

Photosynthesis



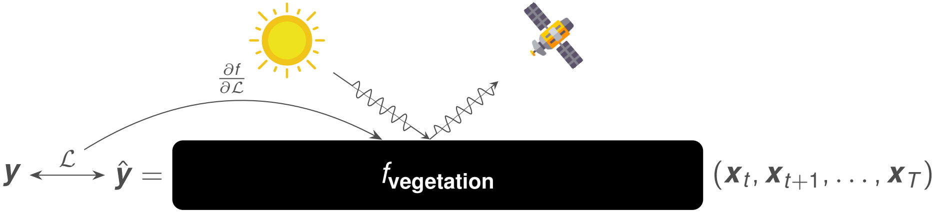
$$\hat{y} = f_{\text{vegetation}}(\boldsymbol{x}_t, \boldsymbol{x}_{t+1}, \ldots, \boldsymbol{x}_T)$$

Problem: **un/self-supervised learning** of a vegetation model **is difficult**

(Proxy)-Solution: re-framing as **supervised classification** of crop type labels

$\boldsymbol{y} \in \{y_{\text{corn}}, y_{\text{meadow}}, \ldots\}$

Photosynthesis



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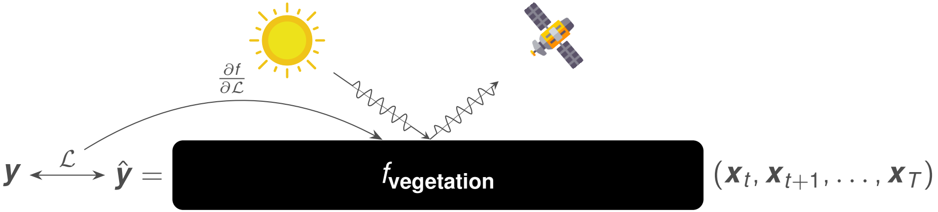

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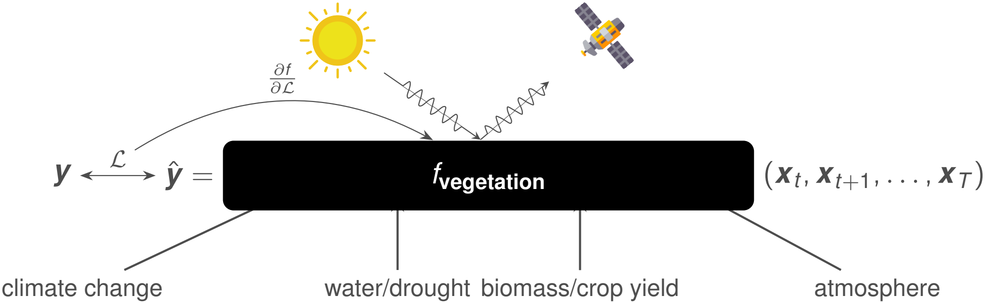
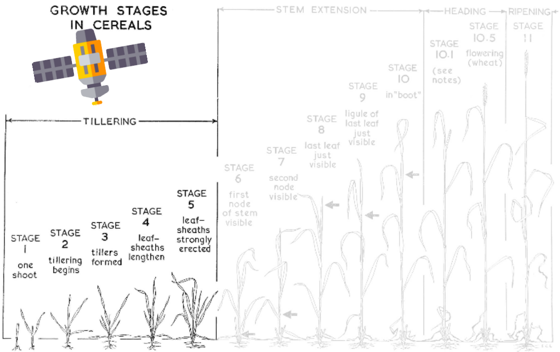
Intuition: A **supervised classification model** must **internalize** a learned **discriminative model** for the **vegetation**

Photosynthesis



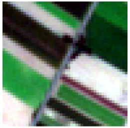
Supervised Crop Classification

Crop Type Mapping



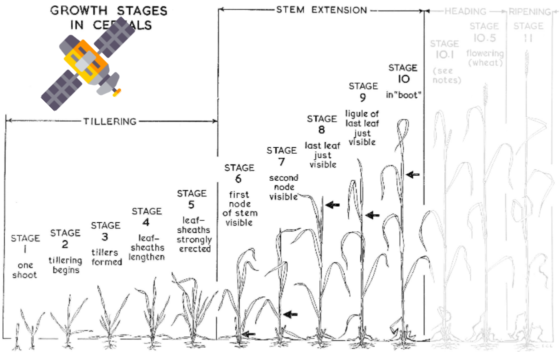
Given a time series of satellite data $\boldsymbol{X} = (\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_T)$ which crop type $\boldsymbol{y} \in y_{\text{corn}}, y_{\text{meadow}}, \ldots$ is cultivated is on the field?

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



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

Crop Type Mapping



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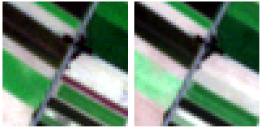

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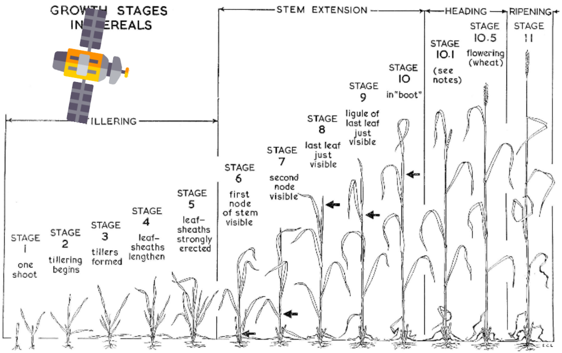

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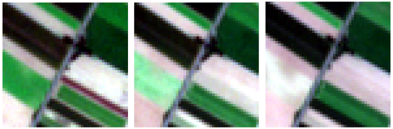

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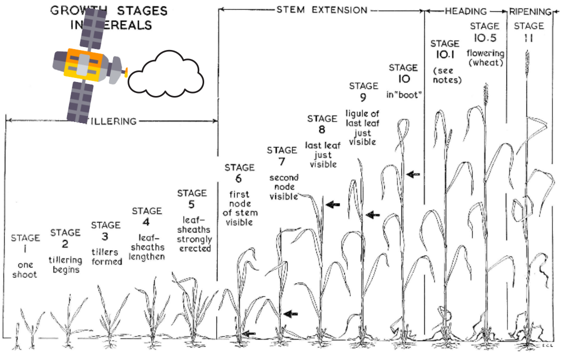

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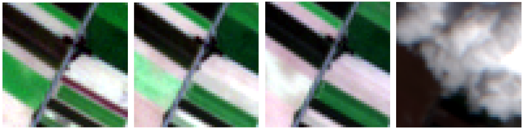

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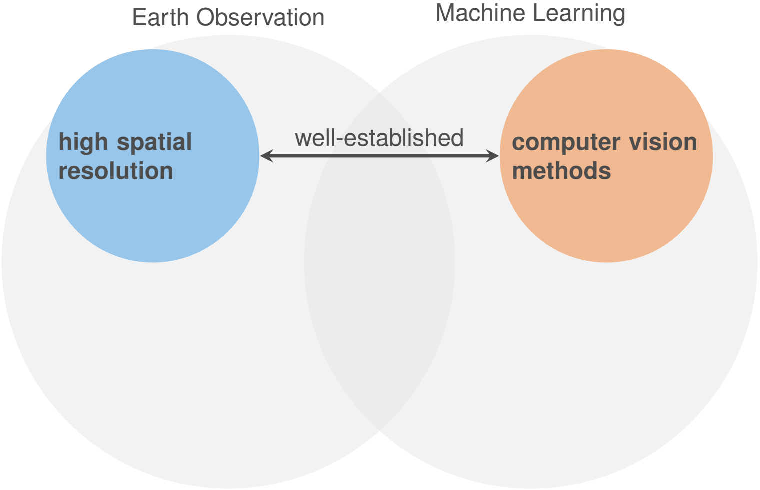
Method Analogies in Machine Learning



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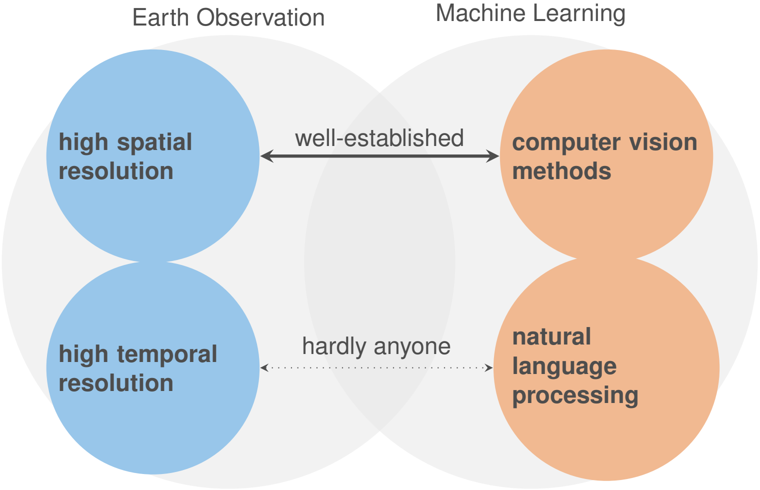

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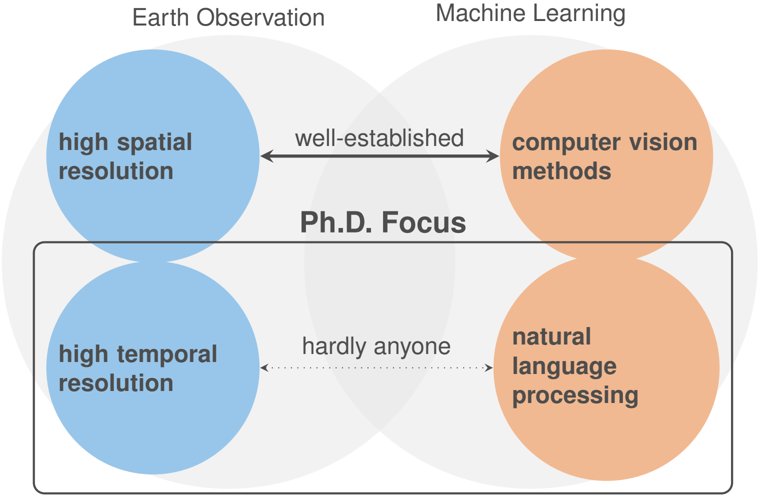
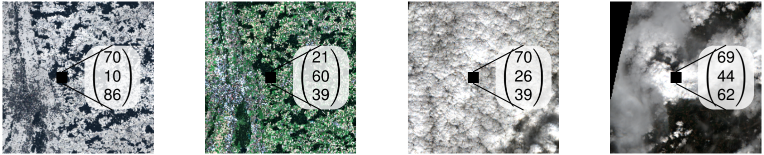


Just Semantic Information Extraction from Sequential Data

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

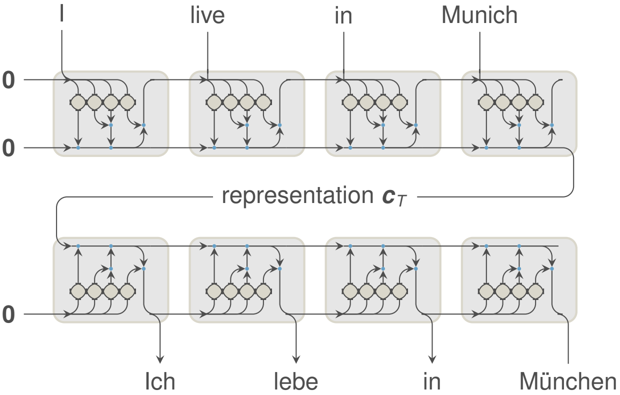


$\xrightarrow{\text{EO model}} f(\boldsymbol{X})$

use same model?

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

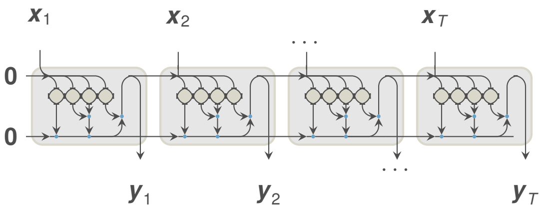
Looking at Sequence to Sequence Models from NLP

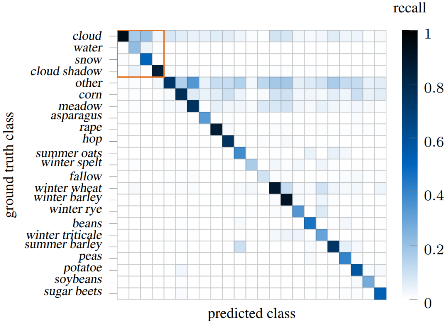


Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to sequence learning with neural networks. In Advances in neural information processing systems (pp. 3104-3112).

Temporal Vegetation Modelling with LSTMs

CVPR Earthvision 2017





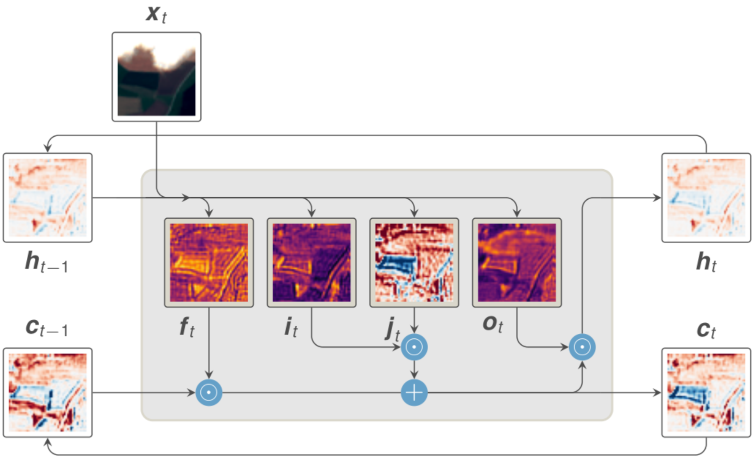
Rußwurm, M. and Körner, M. (2017). ***Temporal Vegetation Modelling using Long Short-Term Memory Networks for Crop Identification from Medium-Resolution Multi-Spectral Satellite Images****. In IEEE/ISPRS EarthVision 2017 Workshop, Proceedings of the IEEE CVPR Workshops.* ***Best Paper Award***

Recurrent Convolutional Neural Networks

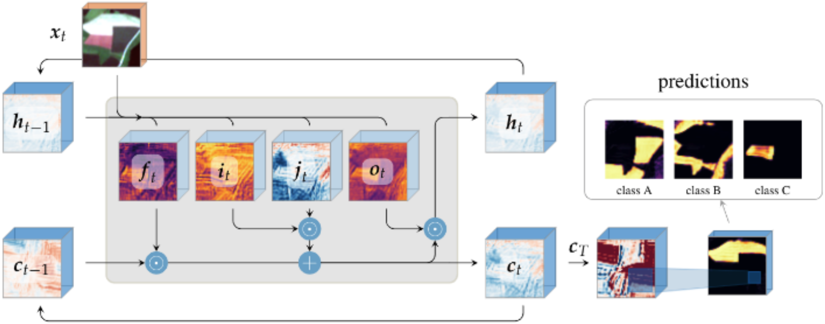
Convolutional Long Short-Term Memory — ConvLSTM (Hochreiter & Schmidhuber, 1997)

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).



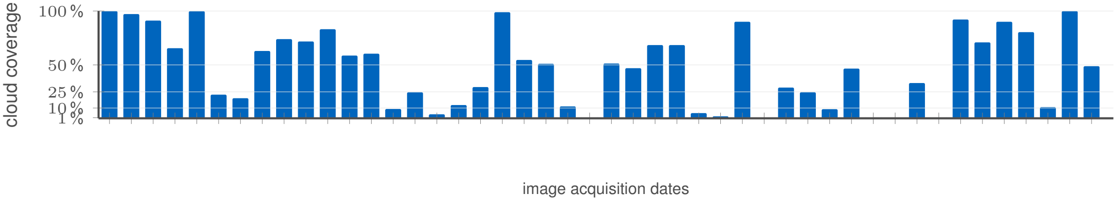
Classification ConvLSTM Network

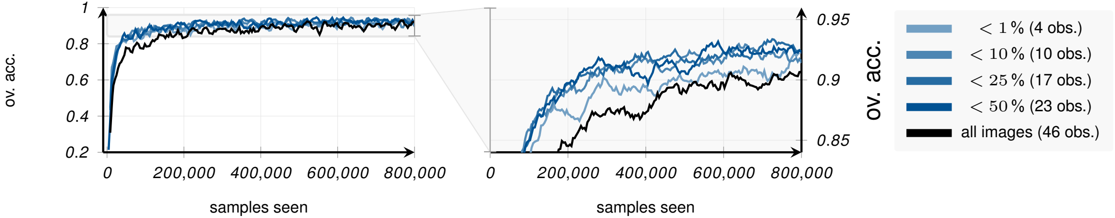


Rußwurm M., Körner M. (2018). ***Multi-Temporal Land Cover Classification with Sequential Recurrent Encoders.*** *In ISPRS International Journal of Geo-Information.*

Surprise: It worked without specifically labeling clouds!

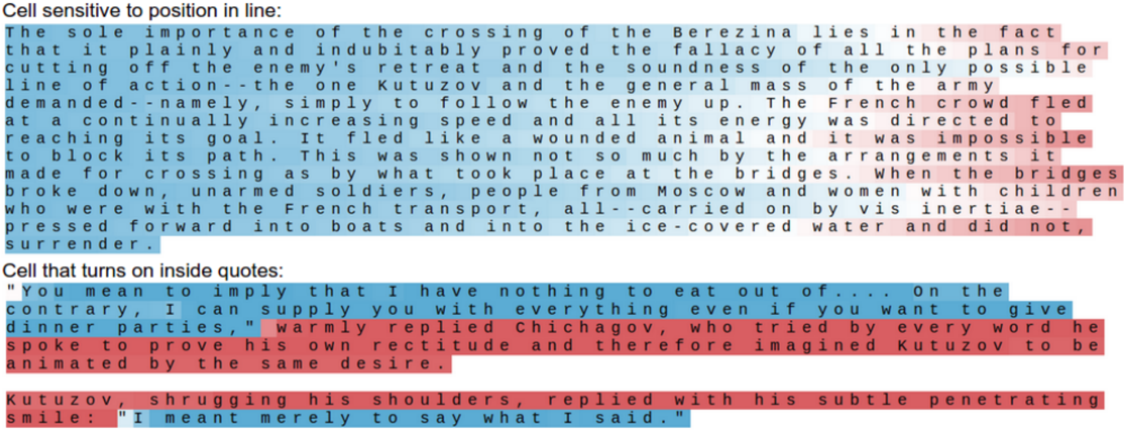
ConvLSTM robust to clouds





*Rußwurm M. and Körner M (2018). **Convolutional LSTMs for Cloud-Robust Segmentation of Remote Sensing Imagery**. NeurIPS 2018 workshop on Modeling and decision-making in the spatiotemporal domain. arXiv:1811.02471*

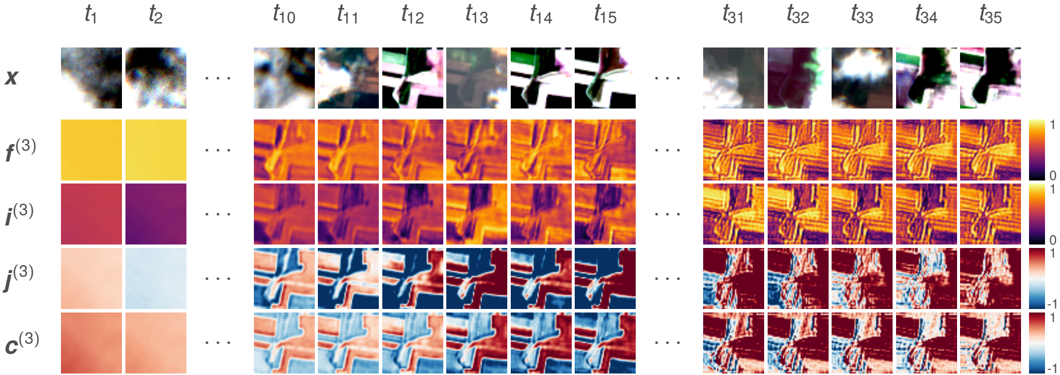
Remembering Karpathy's "Unreasonable Effectiveness of RNNs"



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

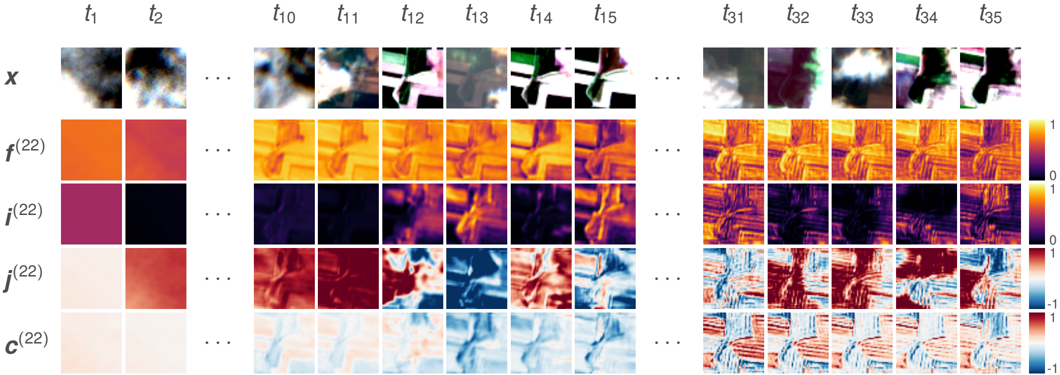
Internal States Encode increasingly Classification Features

LSTM cell **47** of 256



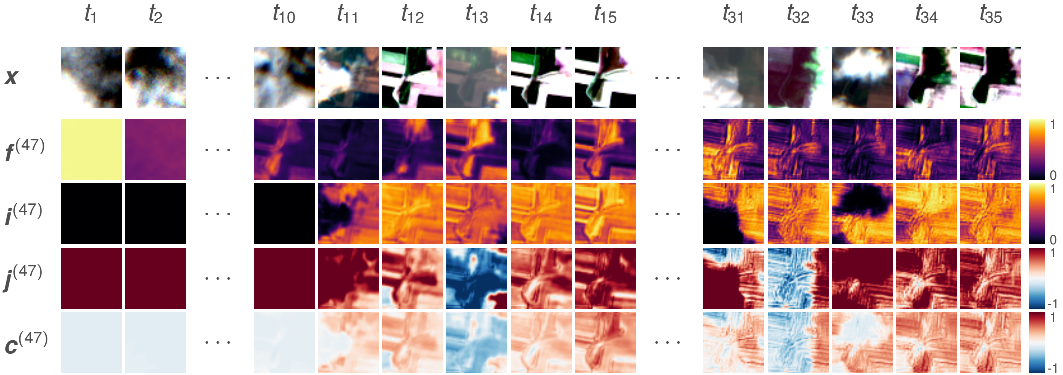
Found Cloud Masking Cells in the RNN

LSTM cell **47** of 256



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

UMR IRISA

Winter Research Stay at IRISA Obelix Lab in France

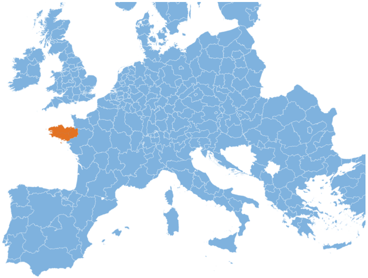
Research Stay Winter 2019

Prof. **Sebastien Lefèvre** and Prof. **Romain Tavenard**

Obelix: **Environment observation** with **complex imagery**

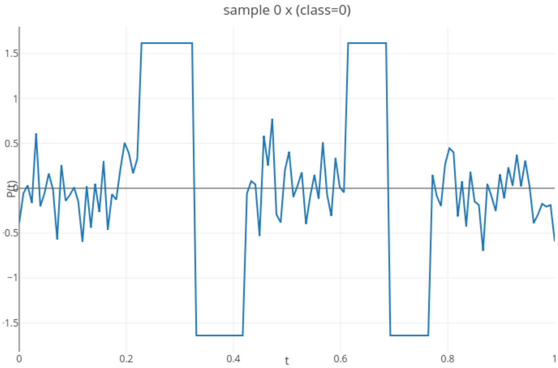
Vannes and Rennes, Britanny, France

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

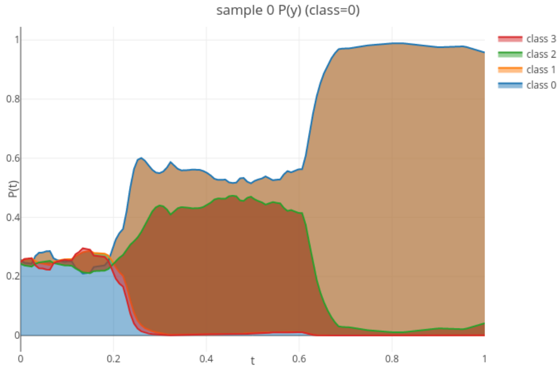


Class Predictions

inputs $\boldsymbol{x}_t$



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



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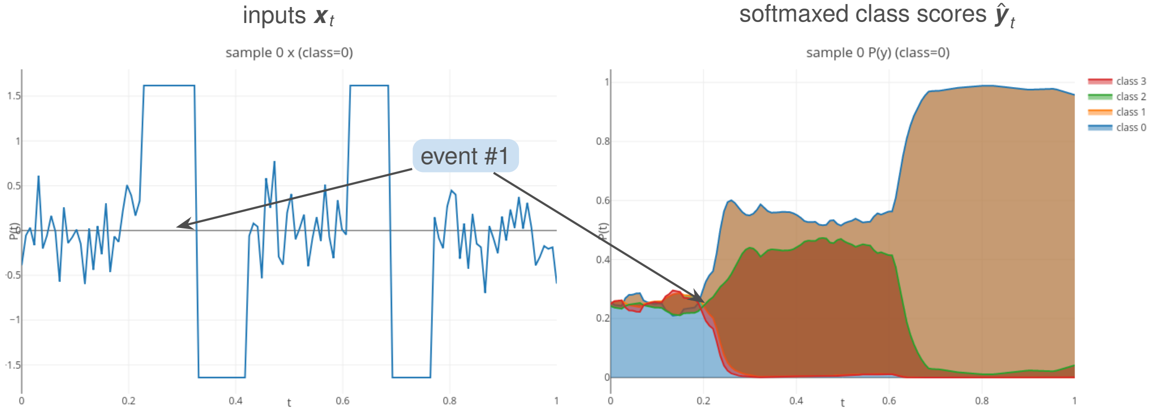

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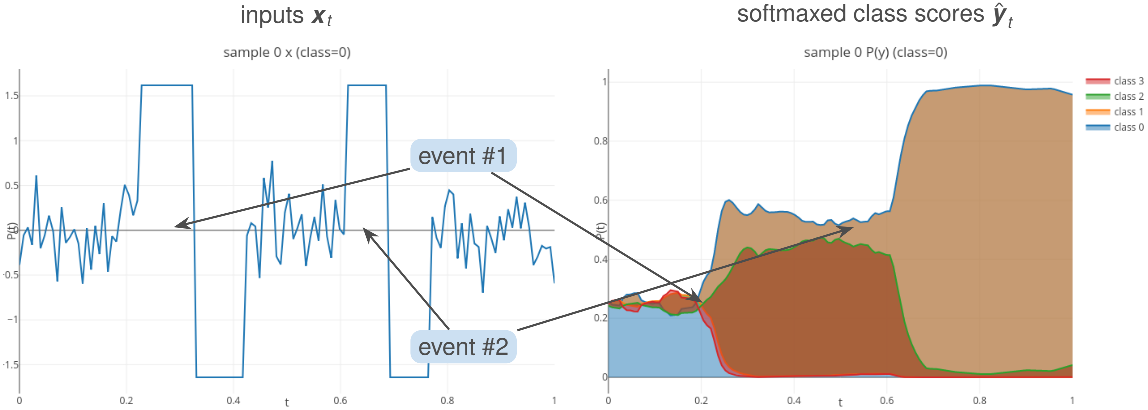

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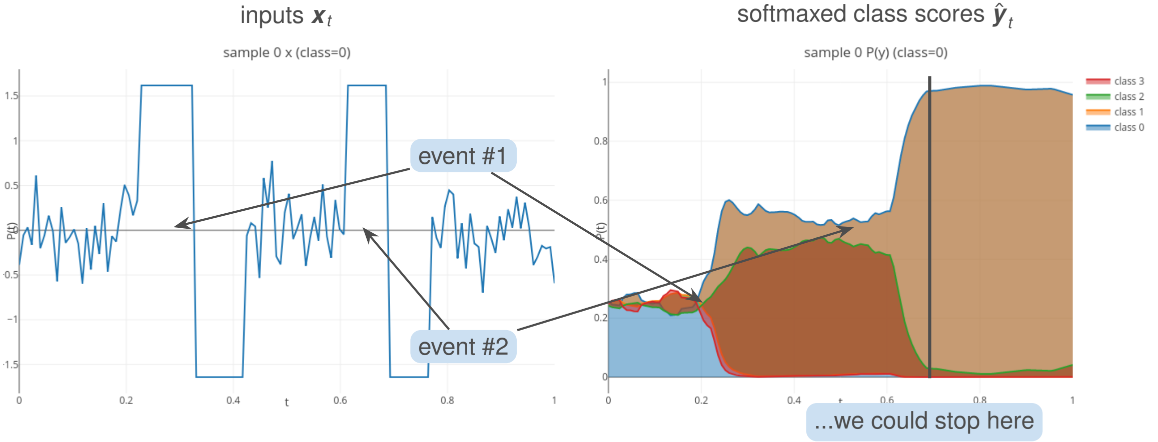
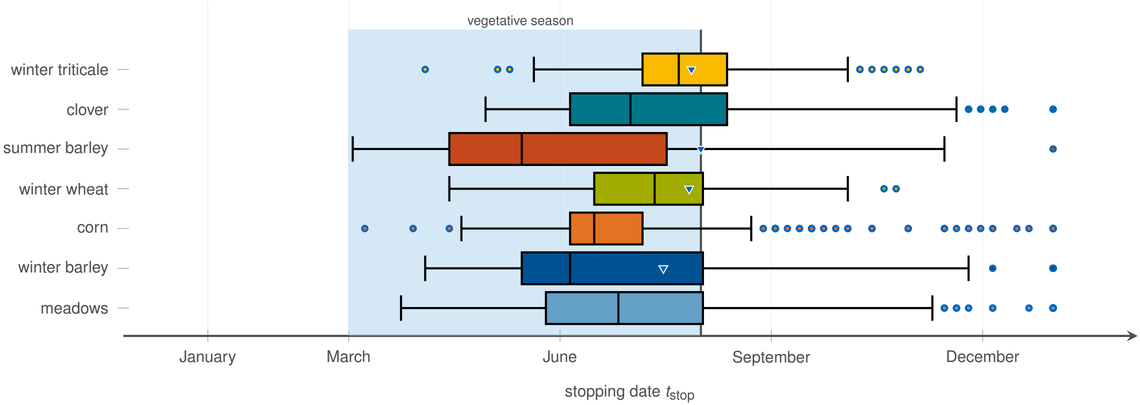


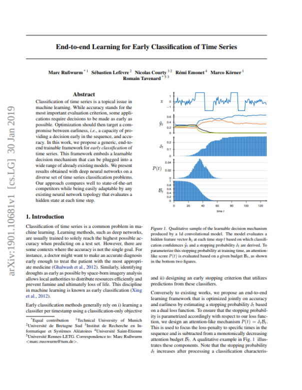
Stopping times per crop Class



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.

https://github.com/rtavenar/early_rnn



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

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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-

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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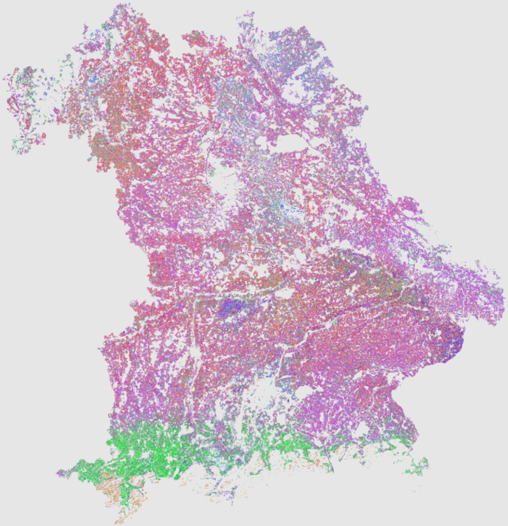


Engaging the ML community

Two Perspectives

Earth Observation

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

method should generalize to applications of a specific sub-field

data has specific **phyisical properties**

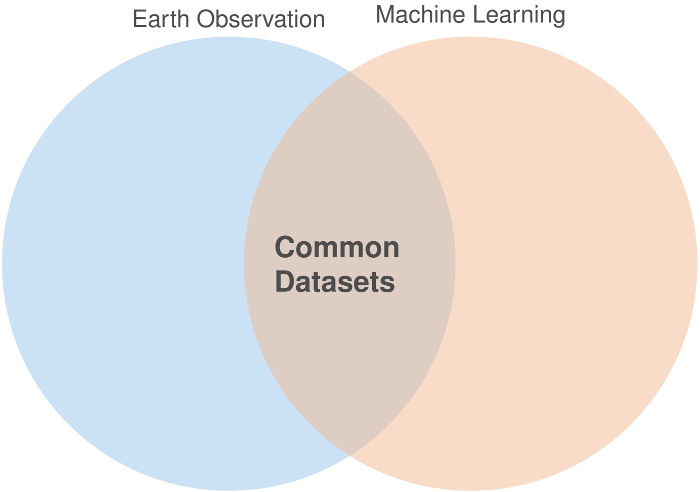
Machine Learning

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

method must generalize to many fields of applications

data is a **feature vector**

Common Datasets



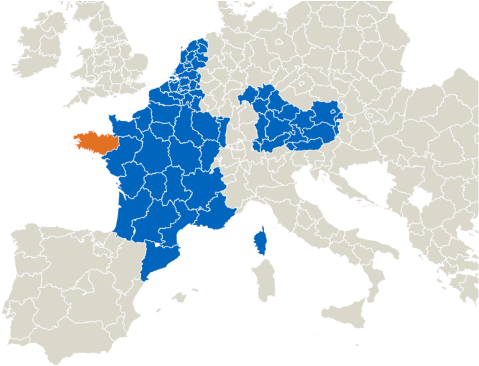
Building Large-Scale Crop Type Mapping Datasets

collected yearly within European **Common Agricultural Policy** (CAP)

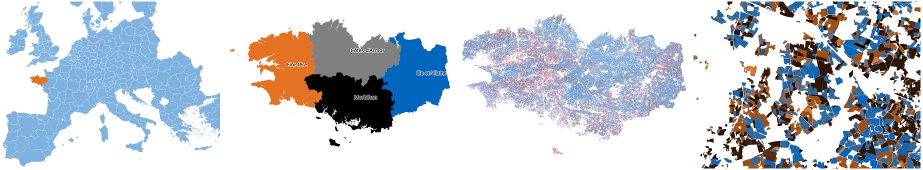
declared by Farmers at **crop subsidy** applications

today slowly made publicly available (on a national basis by French IGN, Bavarian Stmelf, etc.)

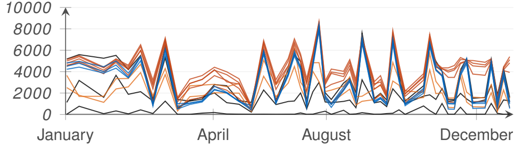
in future further harmonized within **Europe's INSPIRE** directive (correct?)



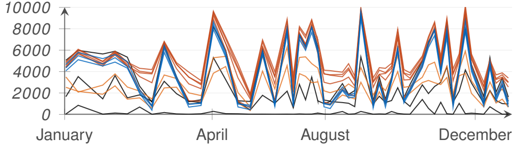
BreizhCrops Dataset (ICML Workshop Submission)



corn grain and silage



temporary meadows



580k samples of Time Series $\boldsymbol{X}$ and labels $\boldsymbol{y}$.
`https://github.com/TUM-LMF/BreizhCrops`

Rußwurm M., Lefèvre S., and Körner M (2019). ***BreizhCrops: A Satellite Time Series Dataset for Crop Type Identification****. ICML 2019 Time Series Workshop. arXiv:1905.11893*

Challenges and Impact

Impact

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

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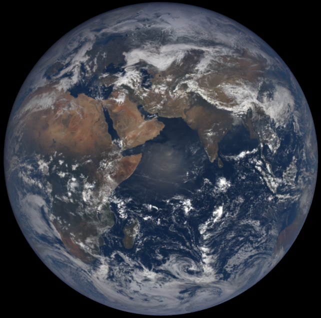
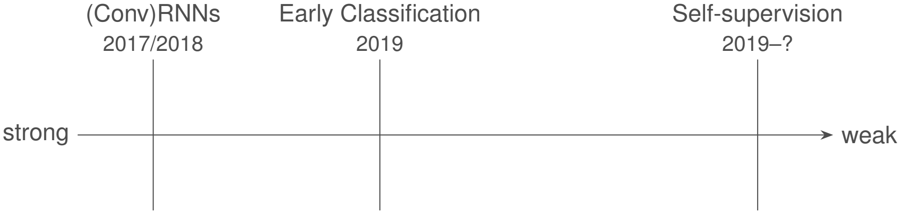
Challenges

- **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



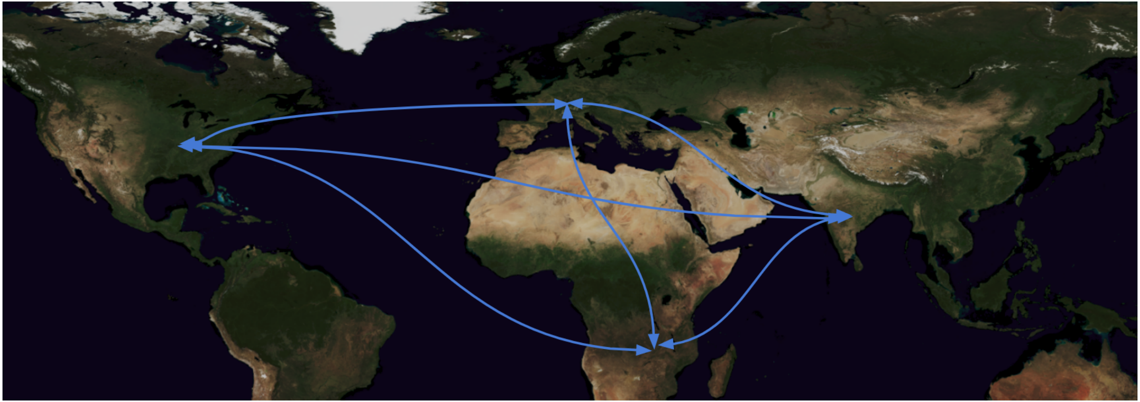
Outlook

Research Agenda – Supervision



Trend: away from strict supervised learning

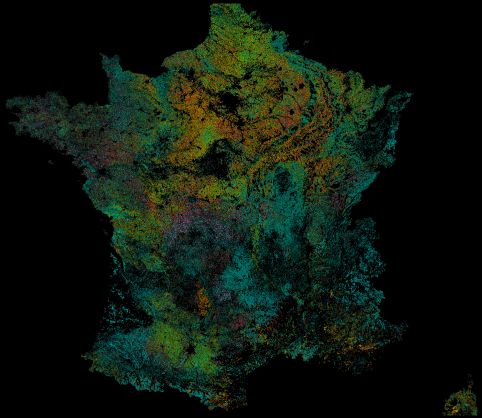
Research Agenda – Generalization



Thank you!

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

`https://marccoru.github.io/`



Questions/Input?

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`https://marccoru.github.io/`

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

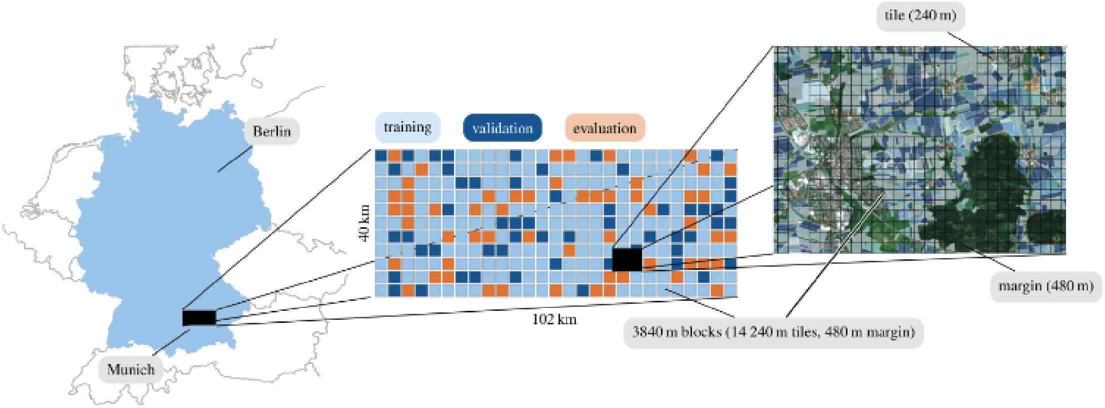
https://twitter.com/MarcCoru

Github

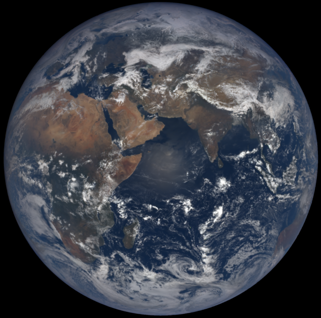
https://github.com/marccoru

https://github.com/TUM-LMF

Area of Interest in Bavaria



Earth Observation Data



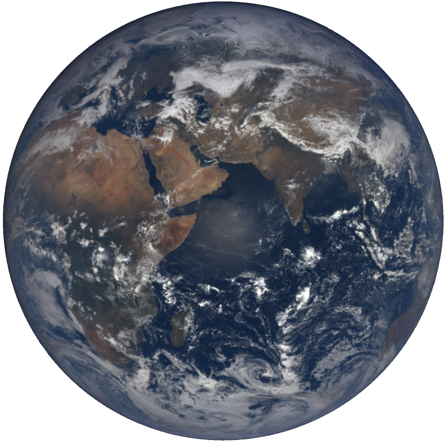
System Earth

Partially measuring System Earth

$\boldsymbol{X} =$  ()

knowledge extraction through pattern recognition and machine learning

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



System Earth

Partially measuring System Earth

Earth Observation Research

$\boldsymbol{X} =$ 🛰(🌍)

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System Earth

Earth Observation Research

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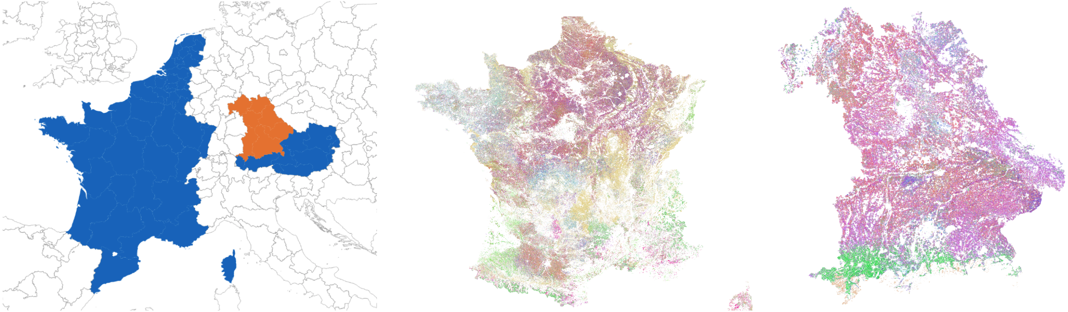
Machine Learning Research

knowledge extraction through pattern recognition and machine learning

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

Going Big...



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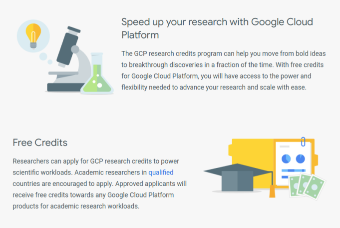
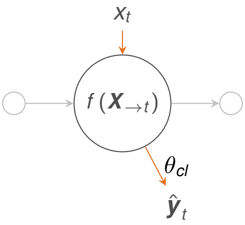
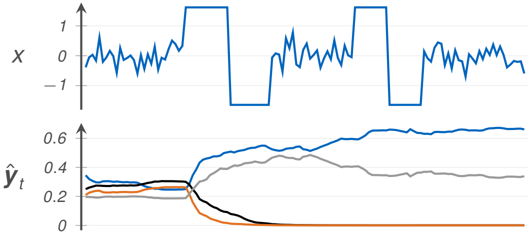


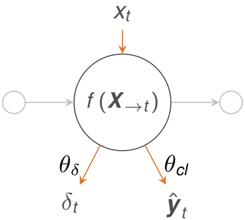
Google

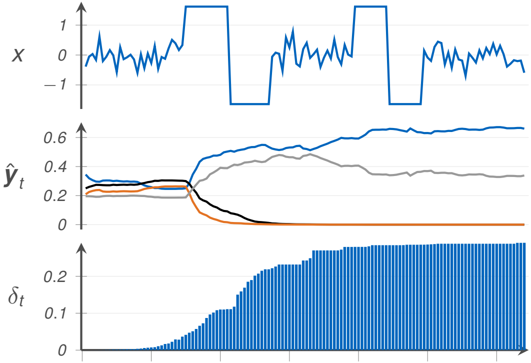
Augmenting Classification Models





Augmenting Classification Models





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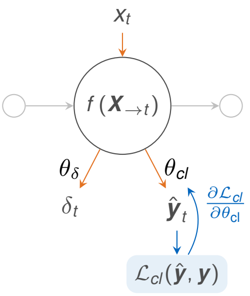

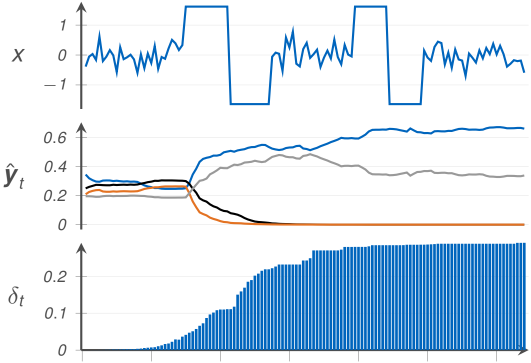

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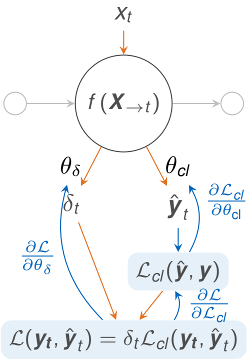

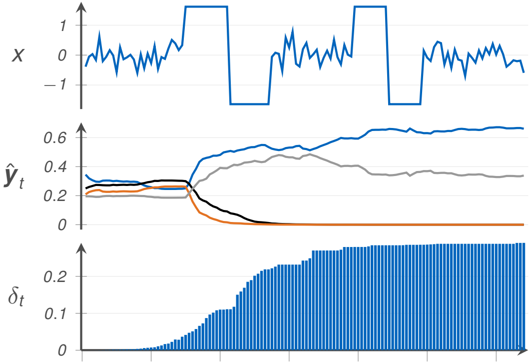

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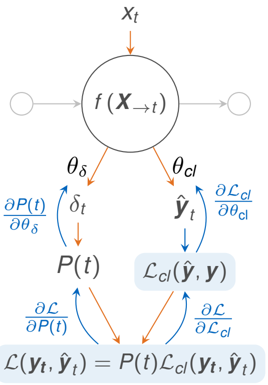
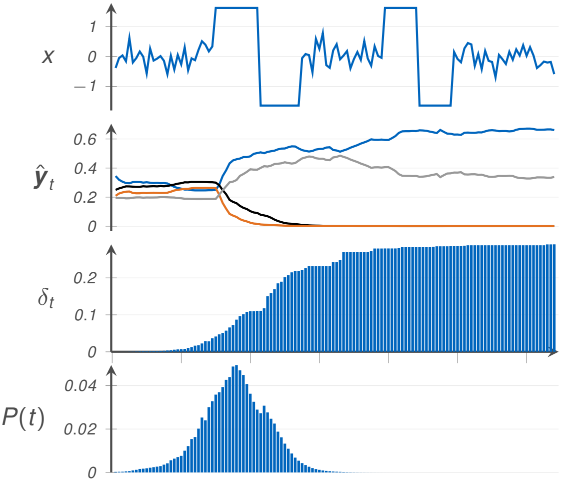
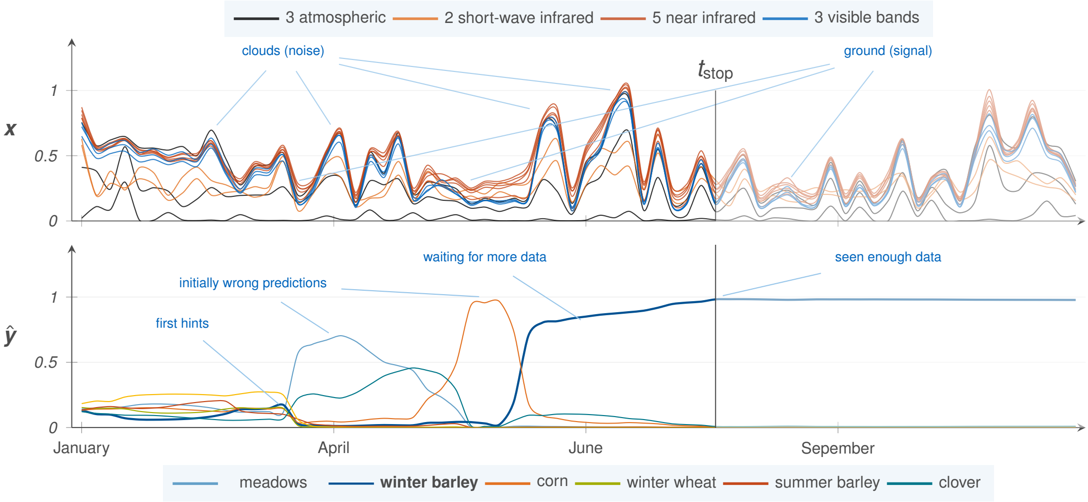


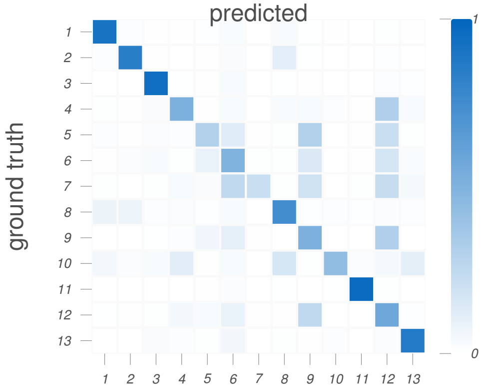


Early Classification on Remote Sensing Data

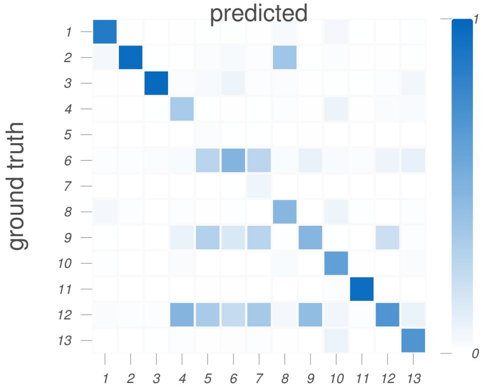


Multi-Layer RNN baseline

Precision



Recall



Transformer baseline