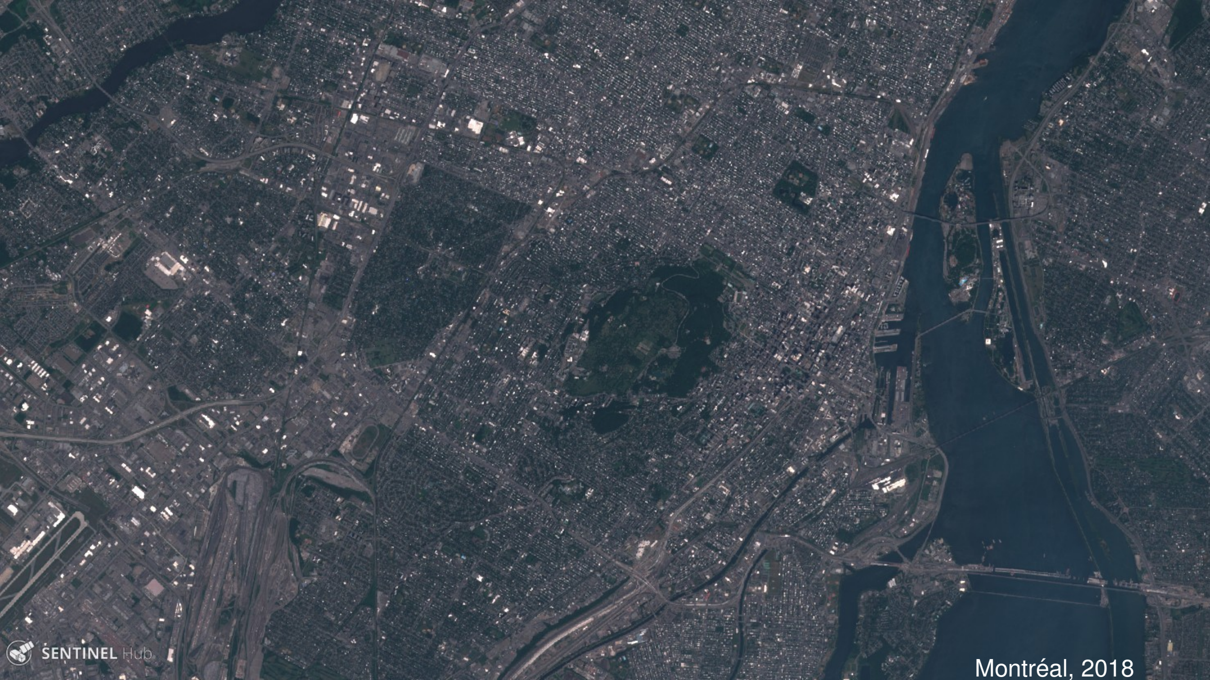
Remote Sensing Technology
TUM Department of Aerospace and Geodesy
Technical University of Munich

Cloud-Robust Classification of Remote Sensing Time Series

Φ-week 2019

Marc Rußwurm, Marco Körner

10th September 2019, ESA ESRIN, Frascati, Italy


SENTINEL Hub
Montréal, 2018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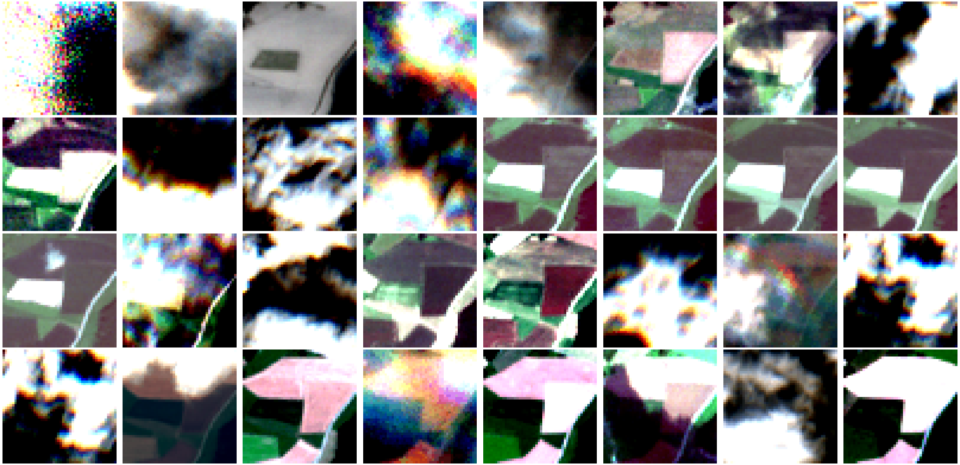
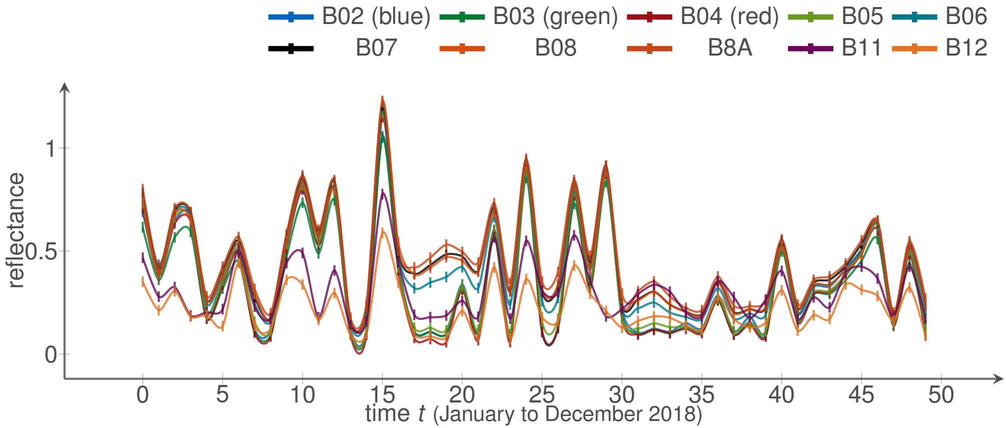
Montréal, 2018

Cloud coverage



Satellite Time Series

Sentinel 2 (raw), mean-aggregated pixels of a meadow field parcel



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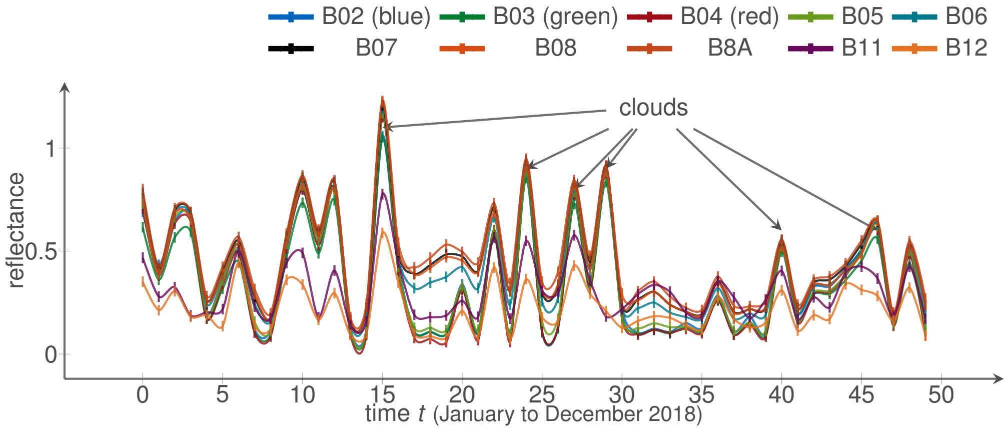

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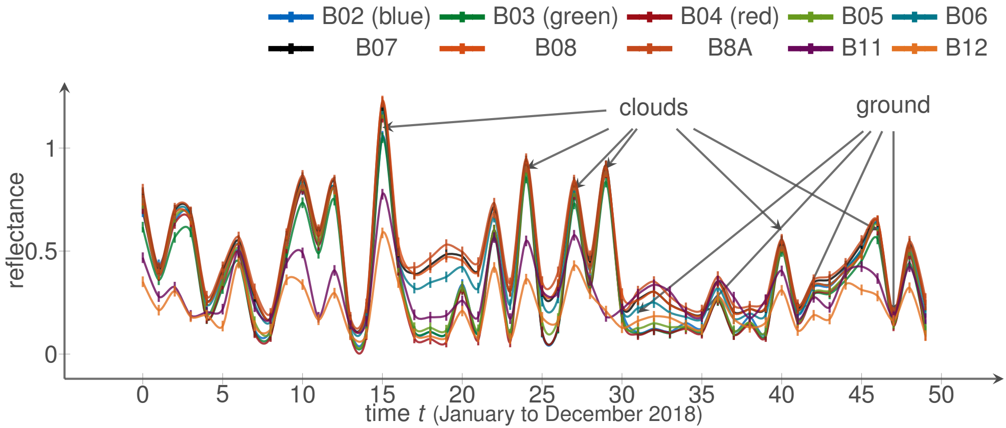
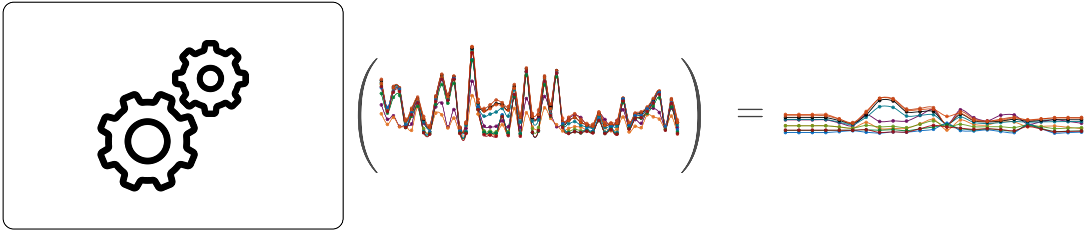


Data Preprocessing



preprocessing

$f_{\theta_{\text{sel}}}(X)$ temporal selection (not considering winter period) where $\theta_{\text{sel}} = \{t_{\text{start}}, t_{\text{end}}\}$

$f_{\theta_{\text{atm}}}(X)$ atmospheric correction ($X_{\text{top-of-atmosphere}} \rightarrow X_{\text{bottom-of-atmosphere}}$)

$f_{\theta_{\text{cl}}}(X)$ cloud/cloud- shadow classification (F-Mask, MAJA, CNNs, Cloud Clustering (go FDL!))

$f_{\text{int}}(X)$ temporal interpolation to generate equal sample times

$f_{\theta_{\dots}}$ **many more problem-specific chained building blocks**

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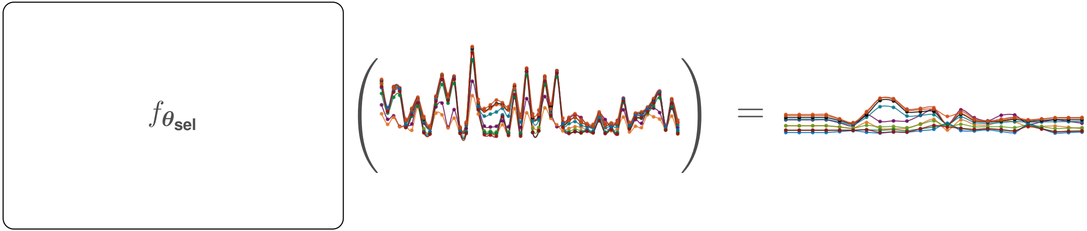

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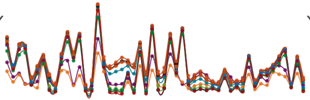
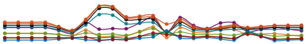
$f_{\theta_{\text{sel}}}\left(f_{\theta_{\text{atm}}}\right)$ $\Bigg($  $\Bigg)$ $=$ 

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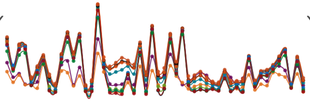
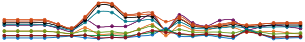
$\Bigg($  $\Bigg)$ $=$ 

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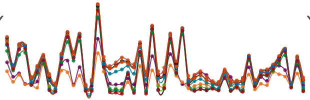
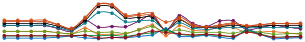
$\Bigg($  $\Bigg) =$ 

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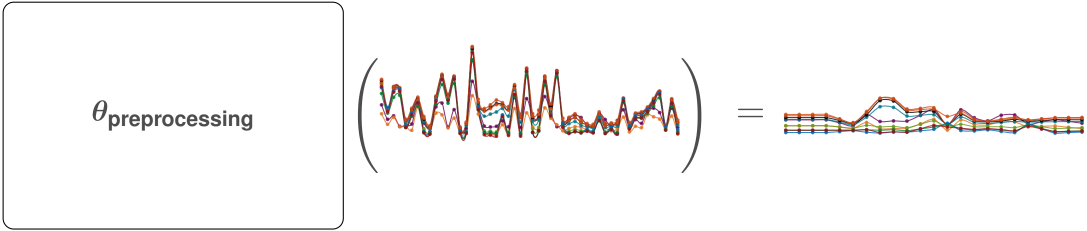

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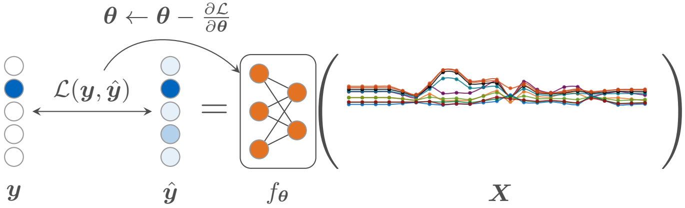
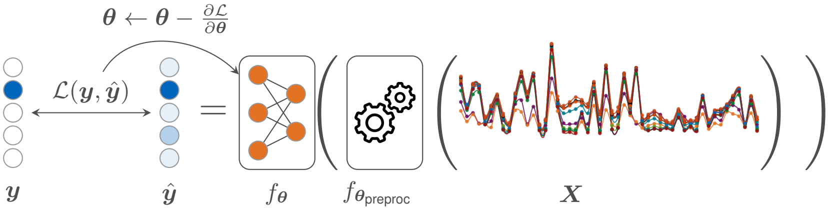
Deep Learning Models are trained differently...

End-to-End Learning of Deep Neural Networks

End — **to** — **End**



End-to-End Learning of Deep Neural Networks



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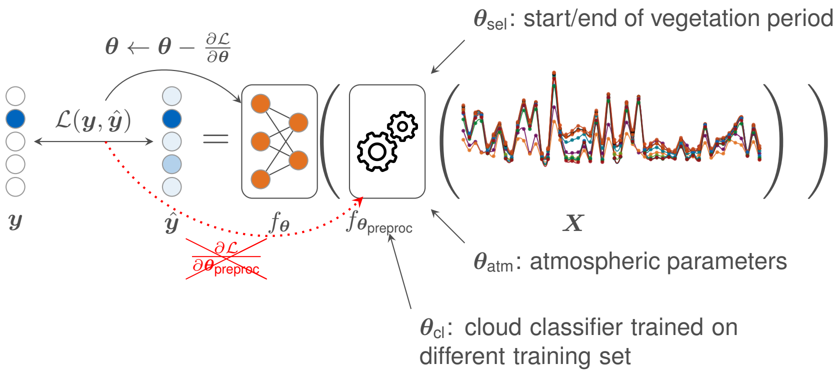

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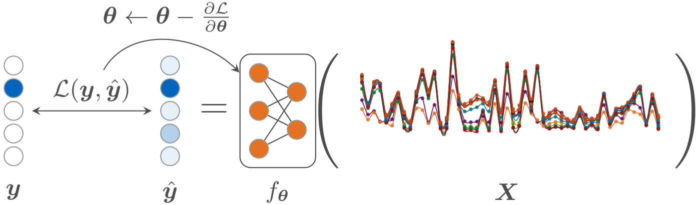
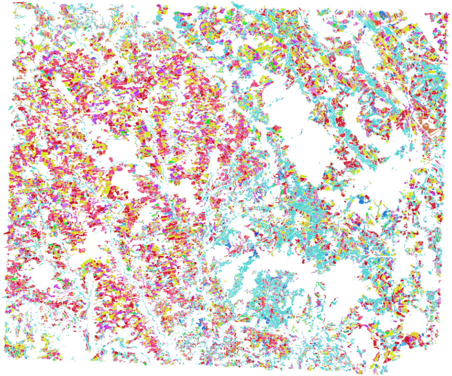


Let’s look at some quantitative results...

Crop Type Dataset northern Bavaria

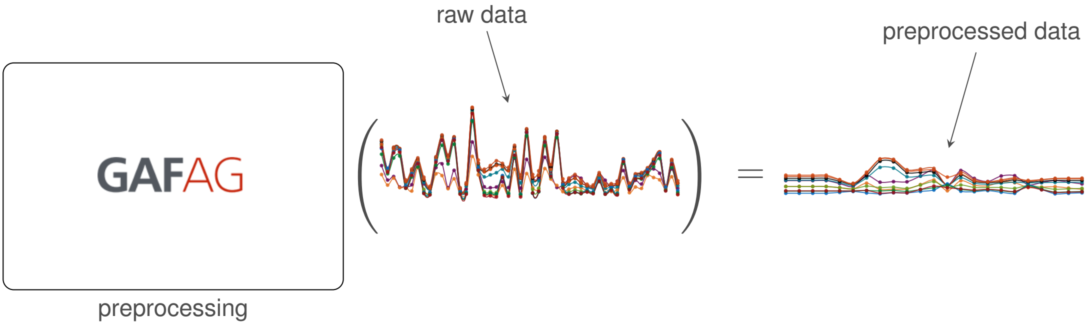
Common project with GAFAG

- crop type labels by the **Bavarian Ministry of Agriculture**
- **49k** field **parcels** of 2018
- **34 crop categories**



Parcels colored by crop type (40 km $\times$ 40 km)

Two Datasets: Raw and Preprocessed from the same Examples



In this case: Preprocessing Engine of GAFAG

Four state-of-the-art deep Models for Time Series Classification

	LSTM-RNN[1]	Transformer[1]	MS-ResNet[3]	TempCNN[4]
Mechanism	Recurrence	Self-Attention	Convolution	Convolution
Parameters	100k	600k	2M	433k

[1] **Hochreiter, S., & Schmidhuber, J. (1997)**. Long short-term memory. Neural computation, 9(8), 1735-1780.
[2] **Vaswani**, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., & Polosukhin, I. **(2017)**. Attention is all you need. In Advances in neural information processing systems (pp. 5998-6008).
[3] **Wang**, F., Han, J., Zhang, S., He, X., & Huang, D. **(2018)**. Csi-net: Unified human body characterization and action recognition. arXiv preprint arXiv:1810.03064.
[4] **Pelletier, C.**, Webb, G. I., & Petitjean, F. **(2019)**. Temporal convolutional neural network for the classification of satellite image time series. Remote Sensing, 11(5), 523.

Preprocessed versus Raw Data

accuracy	RNN (LSTM)[2]	Transformer[3]	MS-ResNet[1]	TempCNN[4]
preprocessed	**.804** $\pm.0031$	.804 $\pm.0011$	**.849** $\pm.0041$	**.836** $\pm.0012$
raw	.801 $\pm.0026$	**.842** $\pm.0043$	.836 $\pm.0033$	.799 $\pm.0027$
Δ	.003 $\pm.0041$	-.038 $\pm.0045$	.013 $\pm.0055$	.038 $\pm.0029$

kappa	RNN (LSTM)[2]	Transformer[3]	MS-ResNet[1]	TempCNN[4]
preprocessed	**.759** $\pm.0037$	.759 $\pm.0017$	**.816** $\pm.0048$	**.799** $\pm.0015$
raw	.756 $\pm.0037$	**.808** $\pm.0052$	.800 $\pm.0039$	.750 $\pm.0036$
Δ	.003 $\pm.0048$	-.049 $\pm.0054$	.016 $\pm.0060$	.049 $\pm.0036$

Experiments:

mean $\pm$ standard deviation of 10 models trained from different random initialization

Findings:

remarkably similar results on preprocessed and raw data ($\Delta \leq 5\%$)

Attention

Photo by zhengtao tang on Unsplash

Self-Attention in Deep Learning

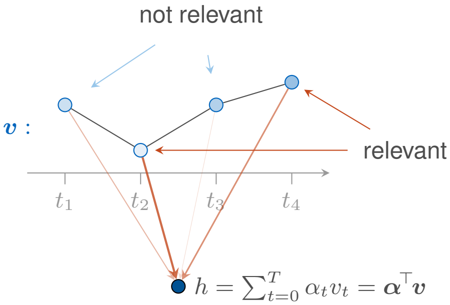
Photo by zhengtao tang on Unsplash

Attention

Given **values** $\boldsymbol{v}$ as a sequence of observations.

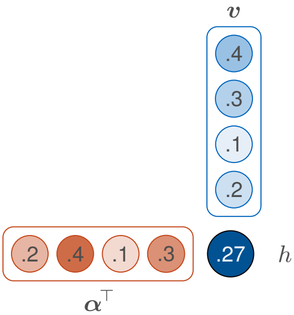
We want to **calculate a result** $\boldsymbol{h}$ based only on **classification-relevant** observations.

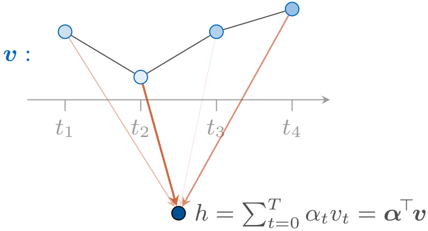
This is realized by an weighted sum over **attention scores** $\boldsymbol{\alpha}$



$$\boldsymbol{h} = \text{Attention}(\boldsymbol{\alpha}, \boldsymbol{v}) = \boldsymbol{\alpha}^\top \boldsymbol{v} = \sum_{t=0}^{T} \alpha_t v_t, \quad \boldsymbol{\alpha} \in [0,1]^{T=4}, \boldsymbol{v} \in \mathbb{R}^T$$

Attention





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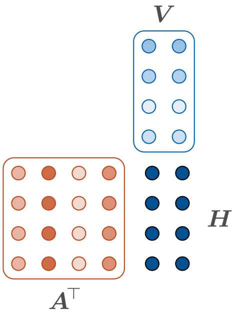
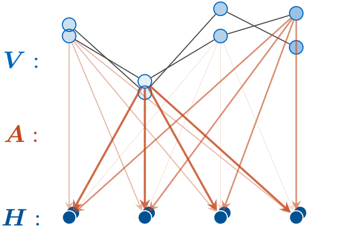
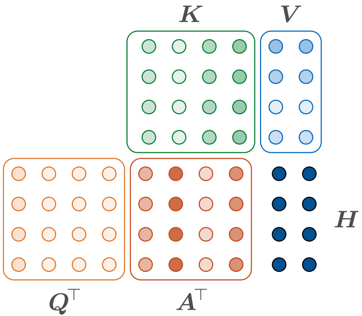
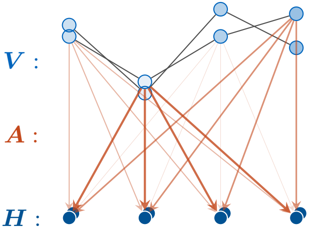




$$\boldsymbol{H} = \text{Attention}(\boldsymbol{A}, \boldsymbol{V}) = \boldsymbol{A}^\top \boldsymbol{V}, \quad \boldsymbol{A} \in [0,1]^{T_{in} \times T_{out}}, \boldsymbol{V} \in \mathbb{R}^{T \times D_v}$$

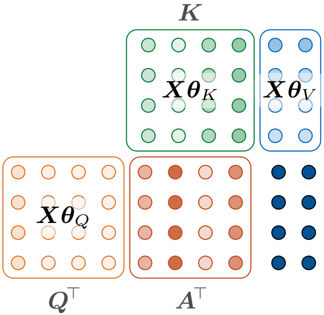
Attention

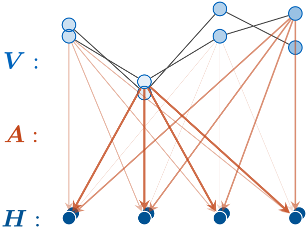




$$\text{Attention}(\boldsymbol{K}, \boldsymbol{Q}, \boldsymbol{V}) = \overbrace{\text{softmax}\left(\boldsymbol{Q}^\top \boldsymbol{K}\right)}^{\boldsymbol{A}^\top} \boldsymbol{V}, \quad \boldsymbol{V} \in \mathbb{R}^{T \times D_v}, \boldsymbol{Q}, \boldsymbol{K} \in \mathbb{R}^{D_k \times T}, \boldsymbol{A} \in \mathbb{R}^{T_{in} \times T_{out}}$$

Self-Attention

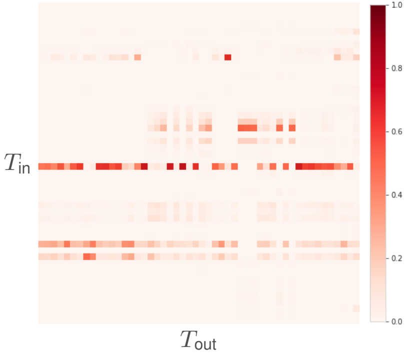




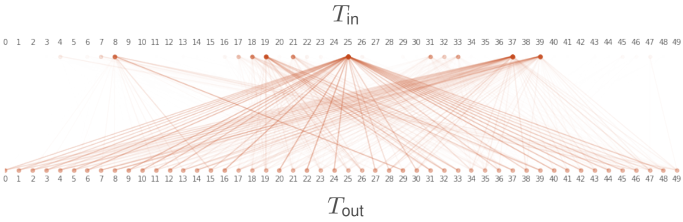
$$\text{Self-Attention}_{\boldsymbol{\theta}}(\boldsymbol{X}) = \text{Attention}(\underbrace{\boldsymbol{X\theta}_K}_{\boldsymbol{K}}, \underbrace{\boldsymbol{X\theta}_Q}_{\boldsymbol{Q}}, \underbrace{\boldsymbol{X\theta}_V}_{\boldsymbol{V}}) = \text{softmax}\left((\boldsymbol{X\theta}_Q)(\boldsymbol{X\theta}_K)\right)(\boldsymbol{X\theta}_V)$$

Visualizing Attention Scores of a Pretrained Transformer Model

As (adjacency) Matrix *A*



As bipartite graph

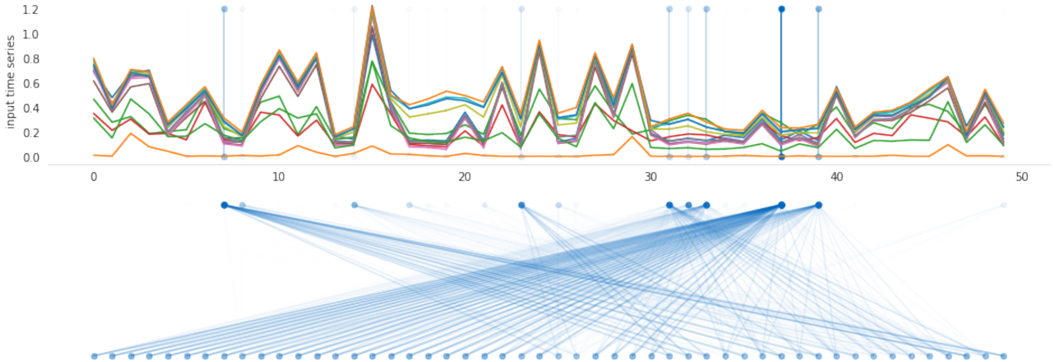


Attention Scores in Context of Input Time Series

Head 1

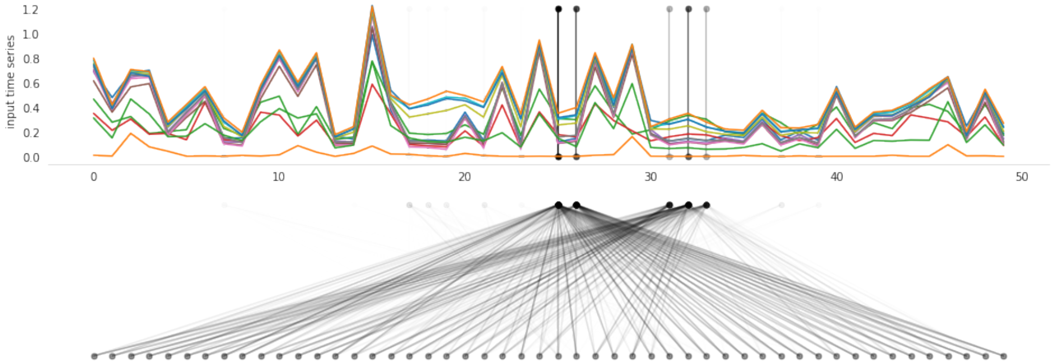
Attention Scores in Context of Input Time Series

Head 2



Attention Scores in Context of Input Time Series

Head 3



Let’s summarize...

Summary

What did we look at?

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end-to-end learning in combination with **preprocessing**

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quantitative **results** on models with **raw** and **preprocessed** data

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quantitative **results** on models with **raw** and **preprocessed** data

a qualitative example on the **self-attention** mechanism

Conclusion

What were the outcomes of these experiments?

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classification results on raw and preprocessed data were **remarkably similar**

do we **need** extensive **preprocessing** for deep learning models on time series data?

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How did deep learning models get robust to noise (e.g., clouds)?

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we saw how **self-attention** is used to **focus** on cloud-free observations

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How did deep learning models get robust to noise (e.g., clouds)?

we saw how **self-attention** is used to **focus** on cloud-free observations

gates in recurrent networks work similar (see previous work)[1,2]

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

[2] Rußwurm, M., & Körner, M. (**2018**). Convolutional LSTMs for Cloud-Robust Segmentation of Remote Sensing Imagery. **NeurIPS2018 Workshop on Spatiotemporal Modeling**

Thank you

Marc Rußwurm & Marco Körner
TUM Chair of Remote Sensing Technology
Computer Vision Research Group

clone the repo to the attention experiments!
github.com/marccoru/phiweek19 Open in Colab

TUM Chair:
www.bgu.tum.de/en/lmf/vision/

our official account:
github.com/tum-lmf

in cooperation with GAFAG

follow **@marccoru** for updates.

github.com/marccoru for code.

and **marccoru.github.io**

Input feature importance analysis through gradient backpropagation

if we change the input $\boldsymbol{X}$...

$$\frac{\partial \max(\hat{\boldsymbol{y}})}{\partial \boldsymbol{X}}$$

Input feature importance analysis through gradient backpropagation

if we change the input $\boldsymbol{X}$...

$$\frac{\partial \max(\hat{\boldsymbol{y}})}{\partial \boldsymbol{X}}$$

... how would the highest predicted score $\max(\hat{\boldsymbol{y}})$ change?

Can be implemented in four lines

```
In [18]: x_ = torch.autograd.Variable(x[None,:,:], requires_grad=True)
         logprobabilities = model.forward(x_)
         logprobabilities.exp().max().backward()
         dydx = x_.grad
```

Gradients from $\max(\hat{\boldsymbol{y}})$ to $\boldsymbol{X}$