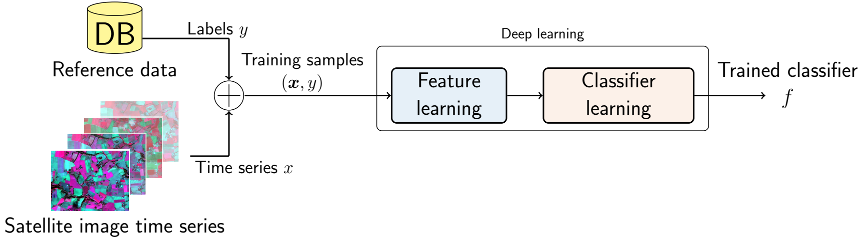
Content

Features are extracted automatically in deep learning



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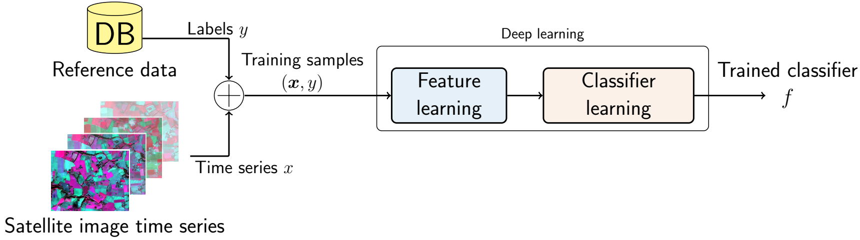
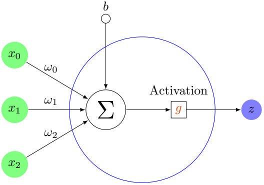


Architecture design is the new feature engineering! One needs to choose

- the type of network,
- the number of layers (depth)
- the number of units per layer (width)
- the learning strategy (optimizer, learning rate)
- *etc.*

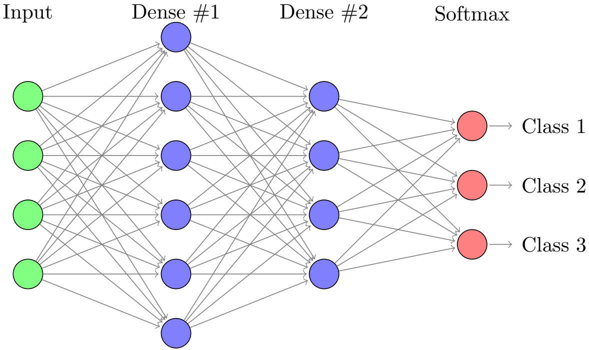
How to train a network?

Training a network = finding parameter values that minimize the cost function



$$y = g\left(\sum_i \omega_i \cdot x_i + b\right)$$

$$y = g(\mathbf{w}^T \mathbf{x} + b)$$



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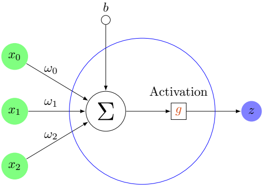

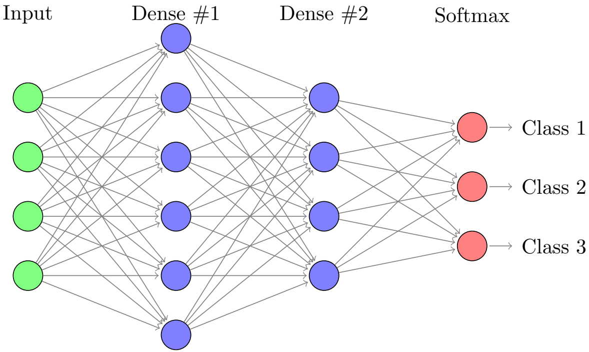

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1. **Forward** step: estimate the cost function

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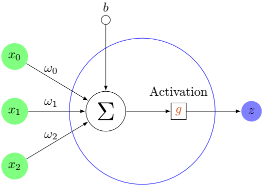

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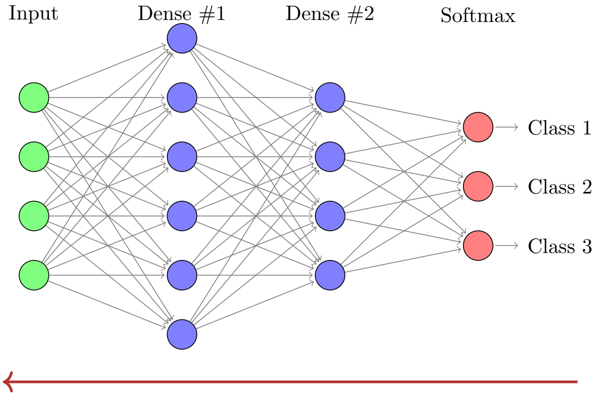
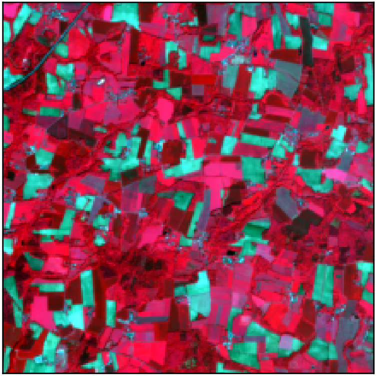


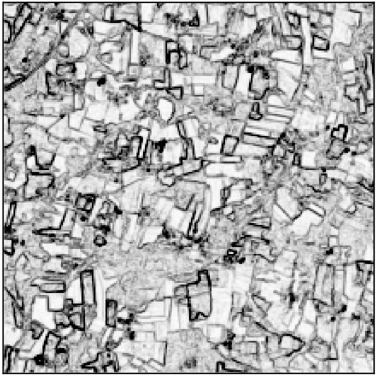
2. **Backward** step: update the parameter values through gradient descent

A. Convolutional Neural Networks

Convolution for images

The convolution is a common image processing techniques for images and signals.





The result of applying a convolution filter (here an edge detection filter) on a Sentinel-2 image.

How it works?

- The result of applying an edge detection on a time series:

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- A convolution (actually a cross-correlation) between a time series x and a filter w at instant t can be expressed as: $(x * w)(t) = \sum_{i+j=t} x_i \cdot w_j$

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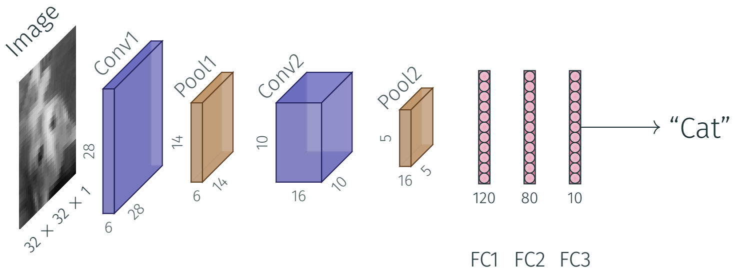
- A convolution (actually a cross-correlation) between a time series x and a filter w at instant t can be expressed as: $(x * w)(t) = \sum_{i+j=t} x_i \cdot w_j$
- Hyperparameters: (i) filter size, (ii) stride, and (iii) padding

- **Learn** the weight of the convolution filter during the network training
- **Stack** several convolution layers
  - first convolution layers extract simple features such as edges
  - last convolution layers extract more complex features



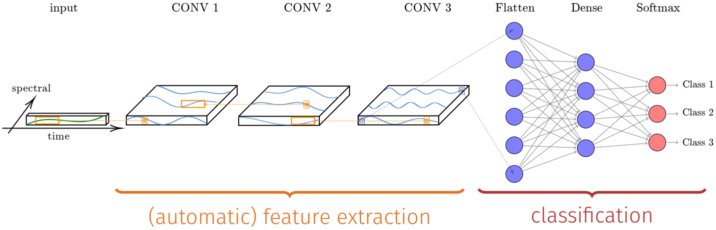
LeNet architecture [1]

[1] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11), 2278-2324.

CNN in remote sensing

Temporal Convolutional Neural Networks (TempCNN) [1]

- fixed filter size
- no pooling layers between convolutional layers



[1] 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.

B. Recurrent Neural Networks

Recurrent Neural Networks

Recurrent Neural Networks (RNNs) are intrinsically designed for sequence data:

- able to explicitly consider the temporal correlation of the data
- state-of-the-art architectures for forecasting tasks

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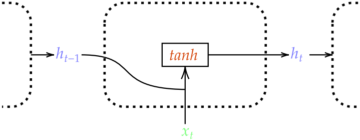
- the state of the recurrent cell is affected by past information h_{t-1} and the current time-series element x_t
- (W_x, W_h, b_h) are the trainable weights and bias learned with backpropagation through time



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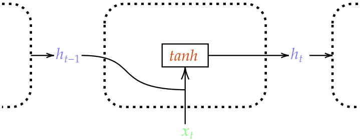


$$h_t = \tanh(W_x x_t + W_h h_{t-1} + b_h)$$

RNNs are good at

- considering past (possibly future) information during computations
- considering time series of different lengths
- sharing weights across time

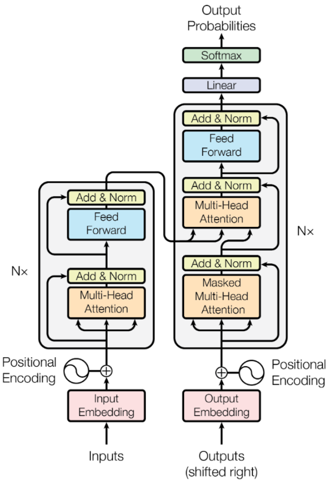
but they are slow to train due to backpropagation through time, and fail to extract long temporal dependencies

C. Attention-based architectures

Transformers

Attention mechanisms were initially proposed by [1], they become popular with Transformers in 2017 [2]

- make the most of GPU
- encoder-decoder architecture similar to RNNs
- develop for language translation or sentence generation

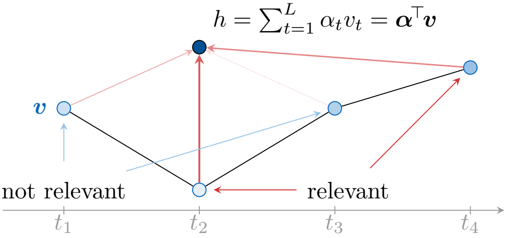


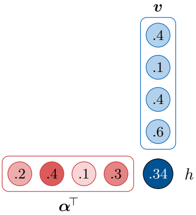
[1] Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473.

[2] Waswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L & Polosukhin, I. (2017). Attention is all you need. In *Conference on Neural Information Processing Systems (NIPS)*

Objective: focusing on the relevant elements of the time series

- Given **values** $\boldsymbol{v} \in \mathbb{R}^L$ as a sequence of observations .
- We want to calculate an output $\boldsymbol{h}$ based only on **classification-relevant** observations.
- This is realized by a weighted sum over **attention scores** $\boldsymbol{\alpha} \in \mathbb{R}^L$.





$$\boldsymbol{h} = \text{Attention}(\boldsymbol{\alpha}, \boldsymbol{v}) = \boldsymbol{\alpha}^\top \boldsymbol{v} = \sum_{t=1}^{L} \alpha_t v_t,$$

$$\boldsymbol{\alpha} \in [0, 1]^L, \boldsymbol{v} \in \mathbb{R}^L$$

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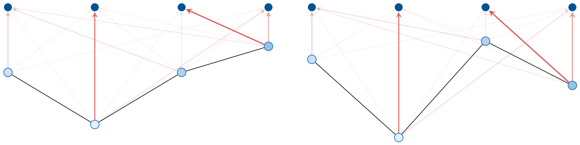

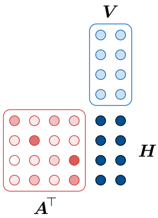

$$H = \text{Attention}(A, V) = A^\top V, \quad A \in [0,1]^{L \times L}, V \in \mathbb{R}^{L \times D_v}$$

where D_v is the dimension of the time series $\boldsymbol{v}$.

How to compute the attention scores?

- We calculate scores from one query $\mathbf{q} \in \mathbb{R}^{D_k}$ and L keys $\mathbf{K} = (\mathbf{k}_t)_{t \in [1,L]} \in \mathbb{R}^{L \times D_k}$

$$\alpha_t(\mathbf{q}, \mathbf{K}) = \frac{\exp\left(sim(\mathbf{q}, \mathbf{k}_t)\right)}{\sum_{\tau=1}^{L} \exp\left(sim(\mathbf{q}, \mathbf{k}_\tau)\right)}$$

- The query $\mathbf{q}$ provides a semantic **context** that is compared to a key $\mathbf{k}_t$ for each sequence element t using a similarity measure *sim*.
- The softmax normalization $\frac{\exp(\cdot)}{\sum \exp(\cdot)}$ ensures that $\sum_{t=1}^{L} \alpha_t = 1$.

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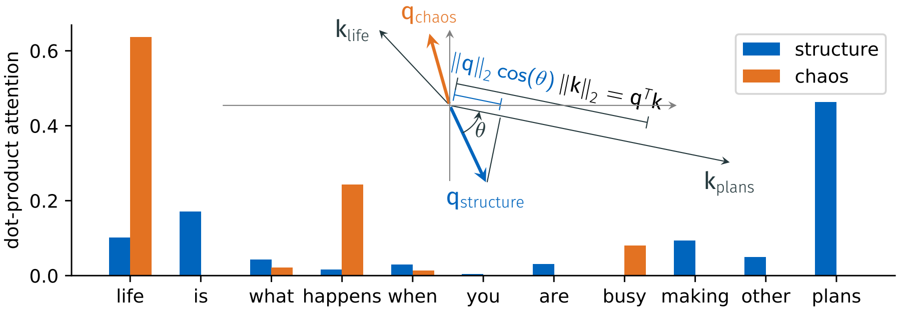
A variety of similarity measures:

cosine distance [1]	$sim(\mathbf{q}, \mathbf{k}) = \frac{\mathbf{q}^\top \mathbf{k}}{\|\mathbf{q}\|_2 \|\mathbf{k}\|_2}$
dot-product [2]	$sim(\mathbf{q}, \mathbf{k}) = \mathbf{q}^\top \mathbf{k}$
scaled dot-product [3]	$sim(\mathbf{q}, \mathbf{k}) = \frac{\mathbf{q}^\top \mathbf{k}}{\sqrt{D_k}}$

Text example

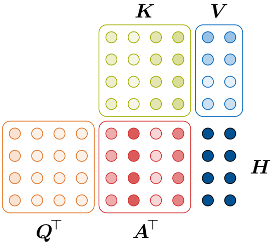
- Each word is embedded into a 300-dimensional semantic Glove Vector, *e.g.*, $\mathbf{e}_{\text{structure}} = E(\texttt{"structure"}) \in \mathbb{R}^{300}$.
- Embeddings of two query words *"structure"* and *"chaos"* are compared to a sentence of keys *"life is what happens when you are busy making other plans"* .



Core idea:

If two words point in the **same direction** ($\theta \approx 0$) attention is **high**.

How to determine the values, keys, and queries?

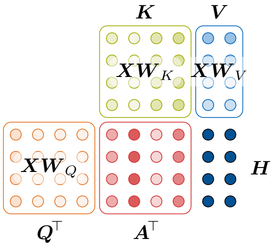


$$\text{Attention}(K, Q, V) = \overbrace{\text{softmax}\left(Q^\top K\right)}^{A^\top} V,$$

$$V \in \mathbb{R}^{L \times D_v}, Q, K \in \mathbb{R}^{D_k \times L}, A \in \mathbb{R}^{L \times L}$$

How to determine the values, keys, and queries?

- the self-attention mechanism uses linear projection of the input sequences X



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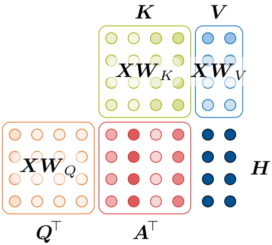
$$\begin{aligned}\text{Self-Attention}_W(X) &= \text{Attention}(XW_K, XW_Q, XW_V)\\ &= \text{softmax}\Big((XW_Q)^T (XW_K) \Big) \Big(XW_V\Big)\end{aligned}$$

Self-attention

How to determine the values, keys, and queries?

◇ the self-attention mechanism uses linear projection of the input sequences X



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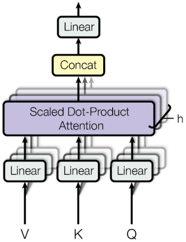
Self-attention is usually applied in parallel heads, which is known as **multi-head attention**.

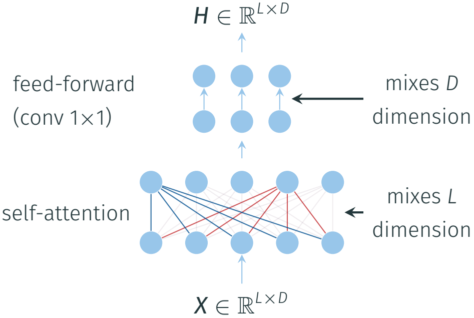


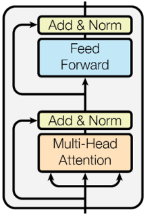
Transformers encoder

The Transformers are composed of **encoder blocks** that map a D-dimensional input times series X of length L into a higher-level representation $H \in \mathbb{R}^{L \times D}$. Each block is composed of:

1. multi-head attention that mixes dimension L
2. feed-forward networks (convolutions of size 1×1) that mixes dimension D

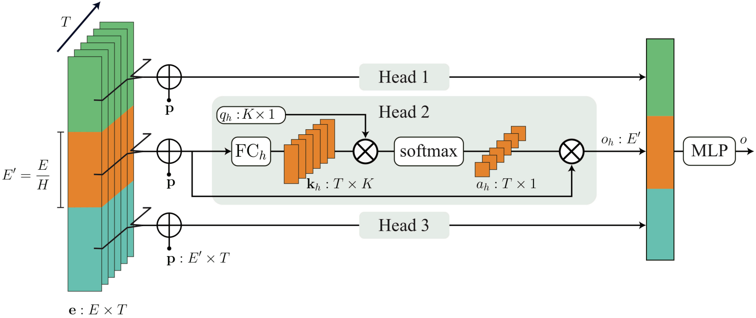
A block also includes skip connections and normalization.





In SITS classification, we want to **predict one label** per time series, not a sequence of words as in sentence translation or generation.

$\Rightarrow$ No need to compute the full attention matrix



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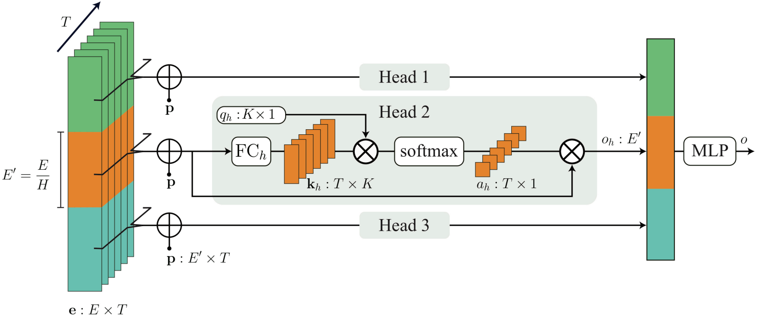

Want to learn more?

- Join us on **Monday** at **2 pm**.
- Loic Landrieux will discuss *Temporal Attention For SITS* in the special session on *Satellite image time series analysis*.

[1] Sainte Fare Garnot, V., & Landrieu, L. (2020, September). Lightweight temporal self-attention for classifying satellite images time series. In *International Workshop on Advanced Analytics and Learning on Temporal Data* (pp. 171-181). Springer, Cham.

Let us now move to the second notebook to put into practice deep learning for satellite image time series

Notebook 2: End-to-End Learning

end-to-end learning	raw data $X \xrightarrow{\text{feature learning}}$ labels y
realization	Sentinel-2 Series $\xrightarrow{\text{deep neural network}}$ crop type y

Link for the notebooks: *https://tinyurl.com/isprs2022*