



Functional Neural Networks

Shift invariant models for functional data with applications to EEG classification

Florian Heinrichs, Mavin Heim, Corinna Weber

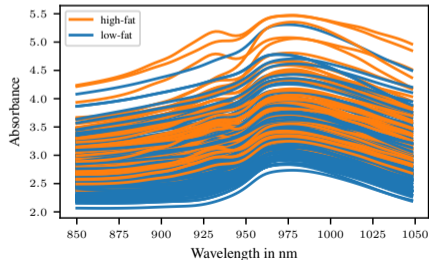
SNAP GmbH

July 2023

Functional Data Analysis (FDA)

1 Functional Data Analysis

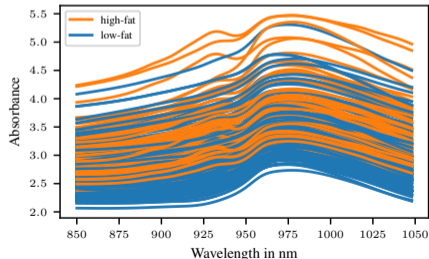
- Example: Classify meat (low-fat vs. high-fat) based on *near infrared absorbance spectrum* (measured at 100 wavelengths between 850 to 1050 nm)



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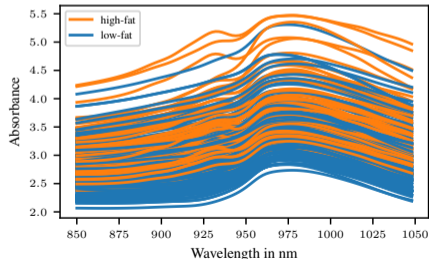
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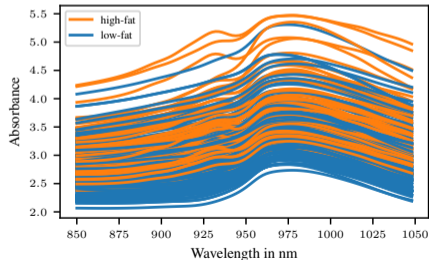
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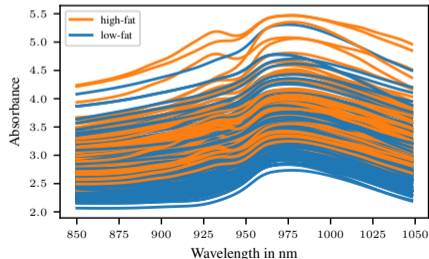
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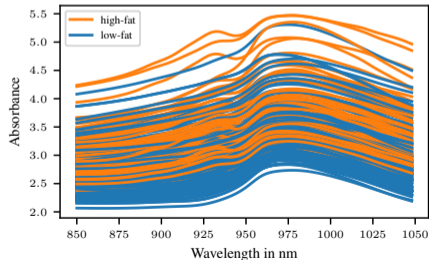
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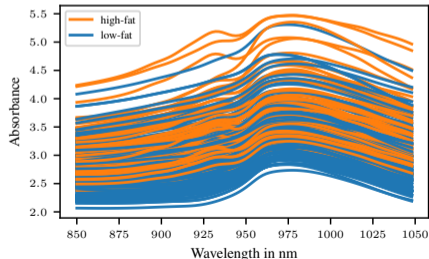
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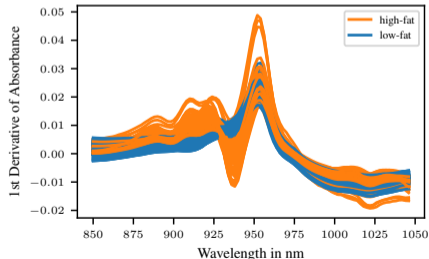
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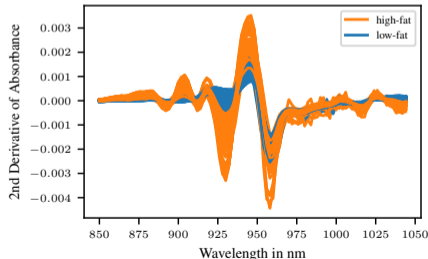
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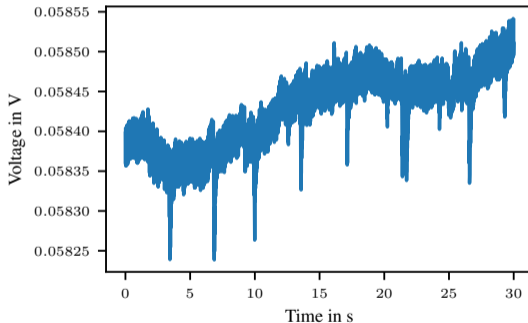




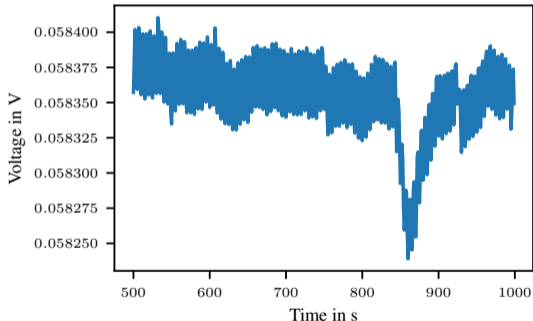
EEG Data

1 Functional Data Analysis

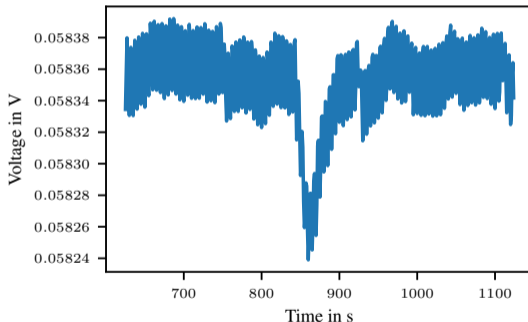
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 - Generally (really) noisy
 - Signal of interest is only weak, has a complex pattern and might occur at any time in a given window



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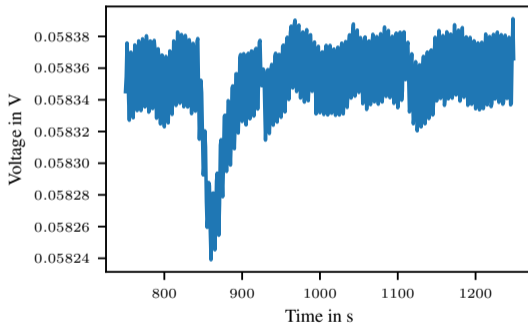
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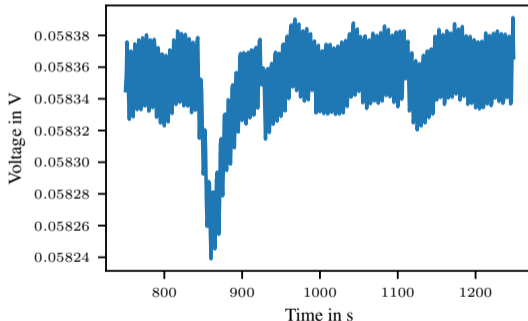
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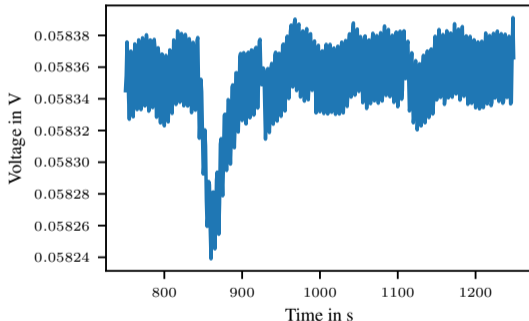
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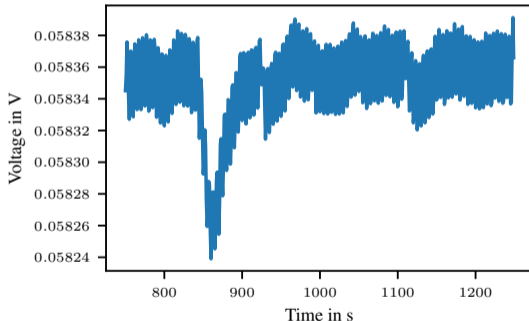
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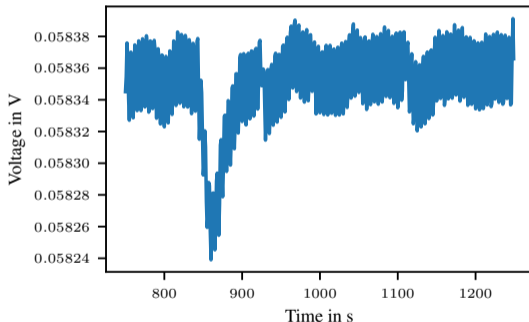
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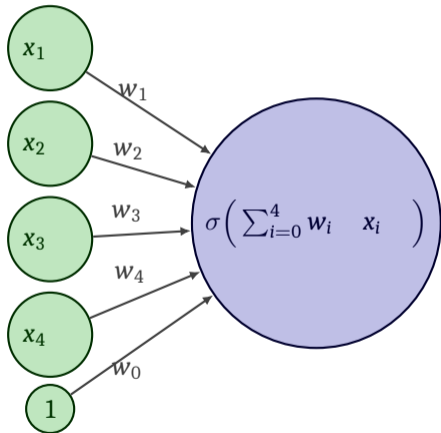
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- In general, neural networks represent data as vectors/matrices
- **Combine deep learning with FDA**



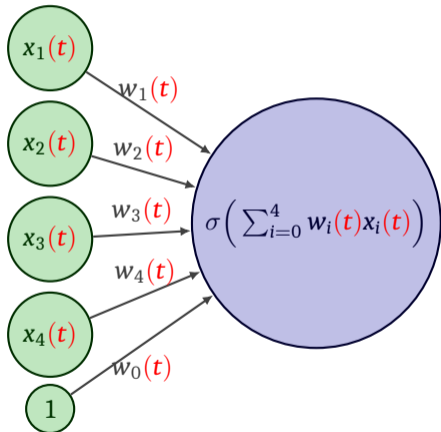
- The output of an artificial neuron is an “activated” linear combination of its inputs



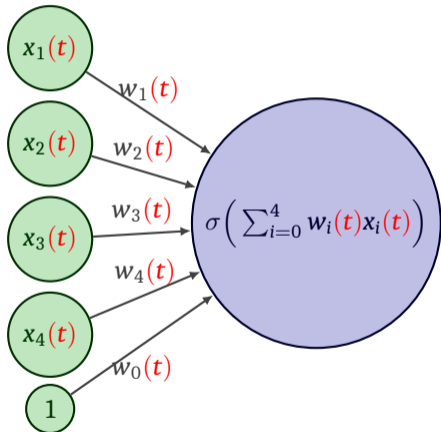
Functional Neurons

2 Functional Neural Networks

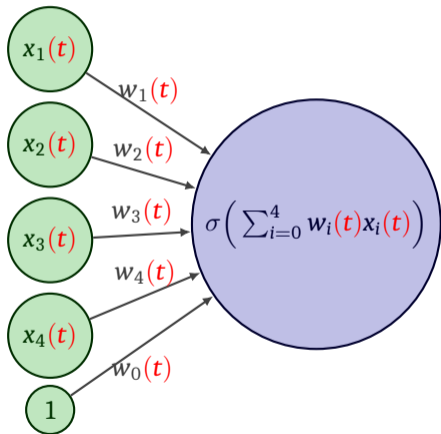
- The output of an artificial functional neuron is an “activated” linear combination of its functional inputs



- The output of an artificial functional neuron is an “activated” linear combination of its functional inputs
- Functional neurons reduce the size of the network and the dimension of its input
 - Consider 4 seconds of an 8-channel EEG with sample frequency 250Hz
 - Vector representation: 8000 numbers
 - Functional representation: 8 functions



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- Other layers can be extended too, e.g. convolutional or pooling layers

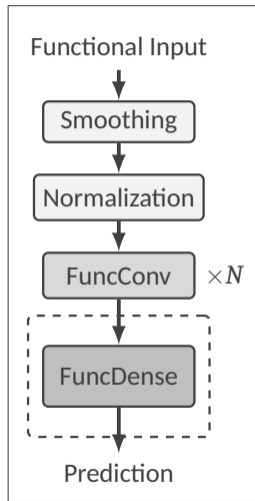




Architecture

2 Functional Neural Networks

- Smoothing: Local linear estimation
- Normalization: Standardizing per channel
- FuncConv: N layers with M filters
 - e.g., $N = 1, M = 20$
- FuncDense: One neuron per class



Empirical Results

2 Functional Neural Networks

- Datasets
 - 2 FDA benchmarks
 - 1 EEG benchmark
 - 2 simulated datasets
- Methods: Neural networks & FDA methods
- Multiple repetitions with random splits
- FNNs achieved state of the art for benchmark datasets

| Model | Accuracy | Recall | Precision |
|--------------------------------------|---------------|---------------|---------------|
| <i>Tecator Dataset</i> | | | |
| CNN | 73.56 | 71.77 | 81.32 |
| MLP | 85.30 | 83.80 | 82.31 |
| FNN(10) | 100.00 | 100.00 | 100.00 |
| FNN(20) | 100.00 | 100.00 | 100.00 |
| Berrendero et al. | 99.53 | - | - |
| <i>Phoneme Dataset</i> | | | |
| CNN | 83.73 | 83.83 | 85.01 |
| MLP | 79.95 | 80.55 | 80.05 |
| FNN(10) | 91.53 | 91.42 | 91.56 |
| FNN(20) | 91.53 | 91.52 | 91.72 |
| Berrendero et al. | 81.14 | - | - |
| <i>BCI Competition IV Dataset 2A</i> | | | |
| EEGNet | 51.81 | 40.21 | 44.75 |
| FNN(20) | 55.43 | 44.98 | 48.31 |
| FNN(40) | 56.29 | 45.95 | 49.46 |







More Details

2 Functional Neural Networks

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- Poster: <https://icml.cc/virtual/2023/poster/25224>
- Paper: <https://openreview.net/pdf?id=vvcJCbxxbp>

-  Berrendero, J. R., A. Cuevas, and J. L. Torrecilla (2016).
The mrmr variable selection method: a comparative study for functional data.
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-  Hastie, T., A. Buja, and R. Tibshirani (1995).
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The Annals of Statistics 23(1), 73–102.
-  Tangermann, M., K.-R. Müller, A. Aertsen, N. Birbaumer, C. Braun, C. Brunner, R. Leeb, C. Mehring, K. J. Miller, G. Mueller-Putz, et al. (2012).
Review of the BCI competition IV.
Frontiers in neuroscience, 55.
-  Thodberg, H. H. (2015).
Tecator meat sample dataset. statlib datasets archive.



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Thank You!