

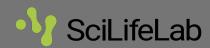


EIVIA 2025: Deep Learning for Time Series and Applications to Healthcare

Gonzalo Uribarri KTH Royal Institute of Technology & SciLifeLab



digital futures





Healthcare Applications

Parkinson's Diagnosis Based on Eye-Tracking Data

Parkinson's disease

- Incidence 83/10000 (+15% since 1990).
- Motor and cognitive symptoms.
- Diagnosis and prognosis methodology is not ideal.

Parkinson's Disease Symptoms



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Parkinson's Disease Symptoms



Our Goal:

Develop a quantitative methodology that can help medical doctors in diagnosis and prognosis.

The Dataset

- ☐ MEG and eye-tracking dataset recorded by **Josefine Waldthaler** and **Per Svenningson** from **Karolinska Hospital** in Stockholm.
- ☐ The dataset consists of 84 subjects, 54 non-demented patients with PD (stages 1-3) and 30 HC.
- Experiment in which two different data modalities are recorded:

- **■** MEG
- Eye Tracking



The Dataset

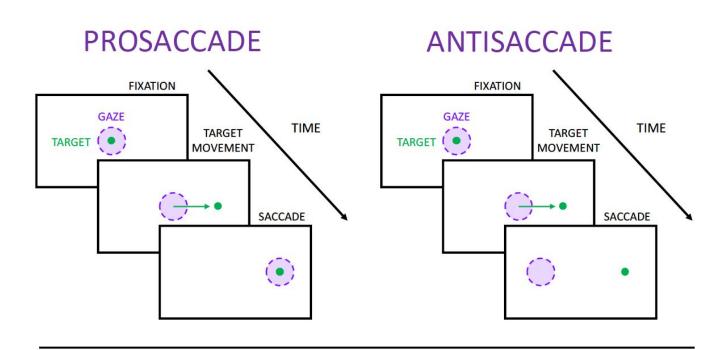
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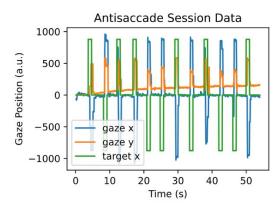
Experimental Protocol

The subjects perform a **Saccade** protocol.



Data description

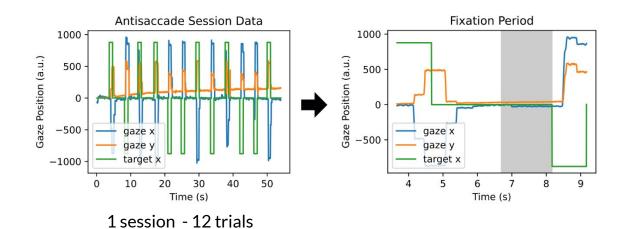
We take ≈1.5s segments corresponding to the **preparation phase** of one saccade or antisaccade event.



1 session - 12 trials

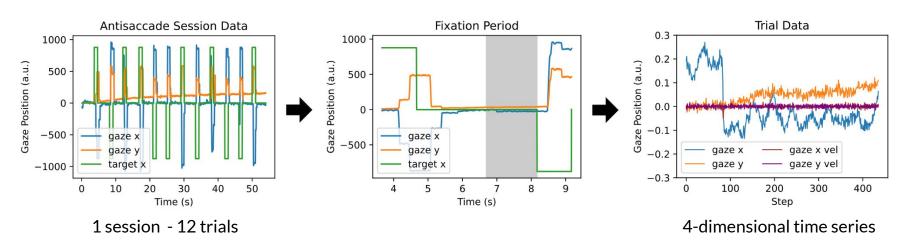
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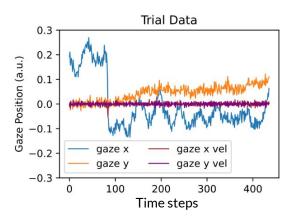
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We have ≈100 trials per subject

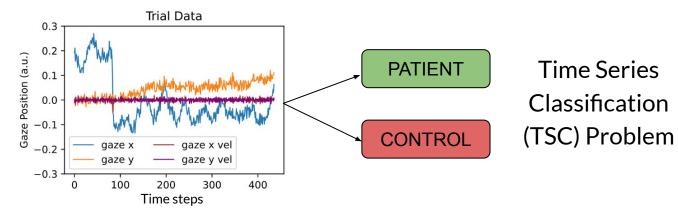
We have ≈1.5s segments of eye movement data corresponding to fixation moments during the experiment.

4-dimensional time series



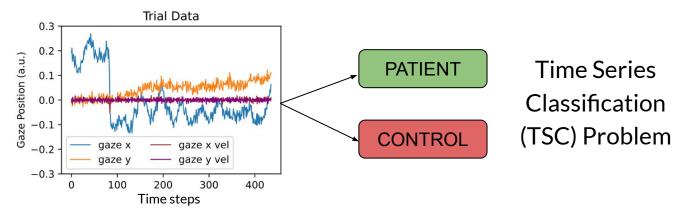
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4-dimensional time series



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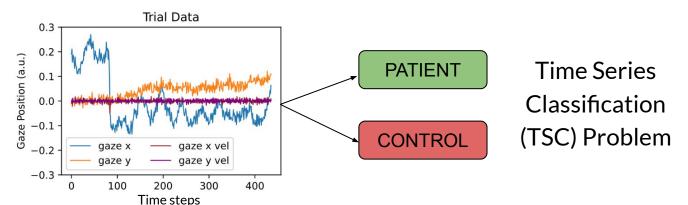
4-dimensional time series



We **100** trials per subject, but we only have **84** subjects.

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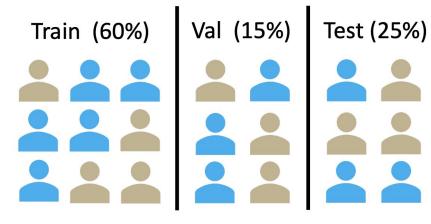


We **100** trials per subject, but we only have **84** subjects.



We need a proper TSC algorithm

Dataset Splitting





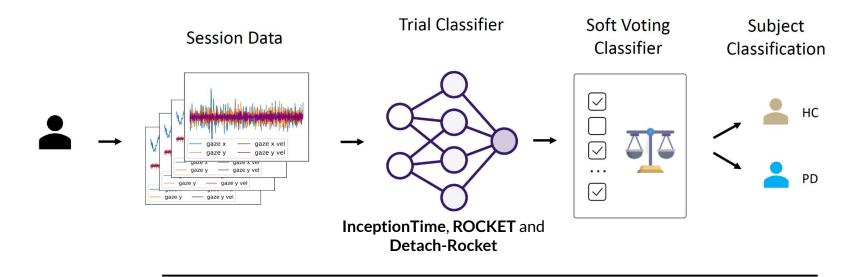
30 - HC



54 - PD Patients (on and off medication)

Inference Pipeline

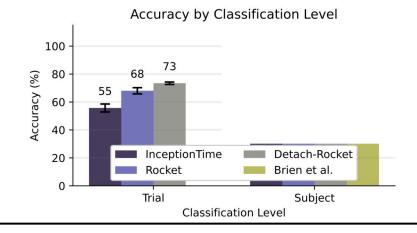
Models are trained to perform a **trial classification**. We then aggregate all trials of one subject to perform a subject classification.



Classification Results

	Trial			
Model	uF1-Score	Accuracy		
InceptionTime	0.52 ± 0.02	$55.73\% \pm 2.84\%$		
ROCKET	0.63 ± 0.02	$68.04\% \pm 2.23\%$		
Detach-ROCKET	0.66 ± 0.02	$73.46\% \pm 0.85\%$		
Brien et al. (2023)				

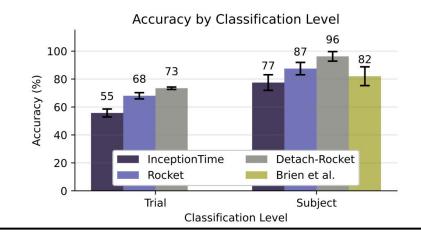
Detach-ROCKET models retained, on average, merely 7% of the original number of features.



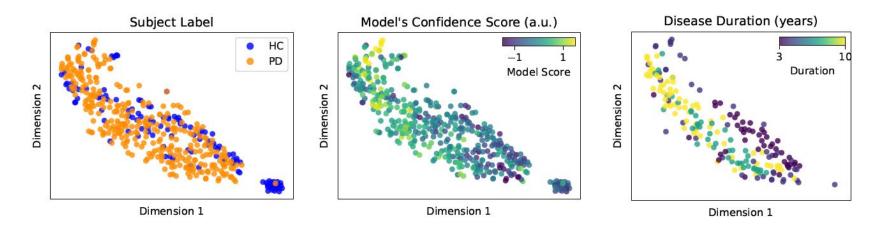
Classification Results

		Trial	Subject		
Model	uF1-Score	Accuracy	uF1-Score	Accuracy	
InceptionTime ROCKET Detach-ROCKET	0.52 ± 0.02 0.63 ± 0.02 0.66 ± 0.02	$55.73\% \pm 2.84\%$ $68.04\% \pm 2.23\%$ $\mathbf{73.46\%} \pm 0.85\%$	0.74 ± 0.04 0.86 ± 0.04 0.96 ± 0.04	$77.50\% \pm 5.59\%$ $87.50\% \pm 4.42\%$ $\mathbf{96.25\%} \pm 3.42\%$	
Brien et al. (2023)				$82\% \pm 6.7\%$	

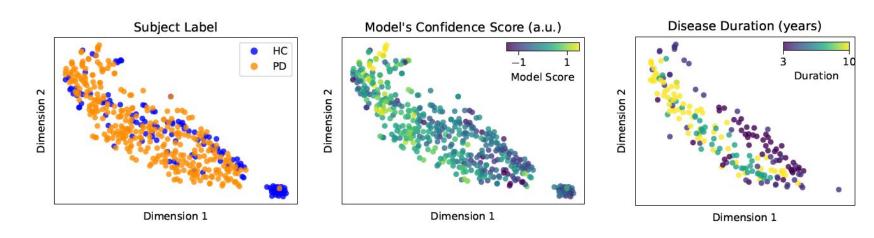
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Exploring the model



Exploring the model



Correlation of model confidence with metadata of patients:

With **UDRS** (severity of symptoms) [c=0.24, p=0.0007 < 0.05]

Correlation

With **disease duration** [c=0.17, p= 0.01 < 0.05]

Correlation

With **age** of patient [c=-0.02, p=0.6 > 0.05]

No Correlation

Brain Activity Data

Brain Activity Data

Brain activity measurements with non-invasive techniques:

• **EEG**: Measures electrical activity.

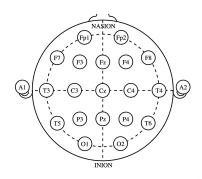
Number of channels: ~19-64.

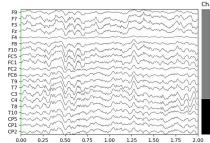
MEG: Measures magnetic activity.

Number of channels: ~306

<u>fMRI</u>: Measures BOLD signal.

Number of channels: ~100,000.





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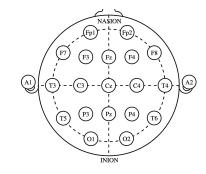
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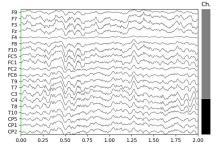
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Large number of channels (C)

ROCKET Strengths and Weaknesses



State-of-the-art performance for TSC



Fast and simple training



Less prone to overfitting (less parameters)



It produces many features (many useless)



Scales poorly with the number of channels



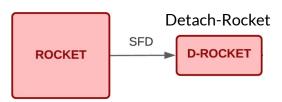


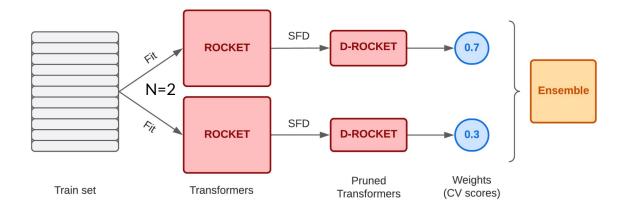
Difficult to interpret

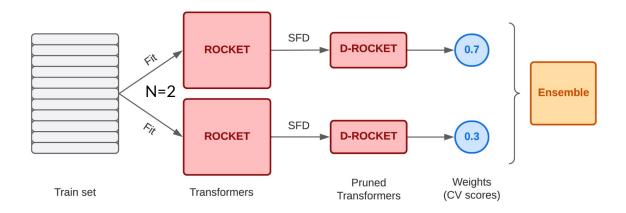
We need a very large number of kernels to have good coverage.





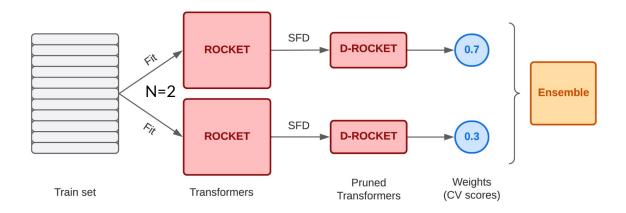








Explores a large set of kernels.

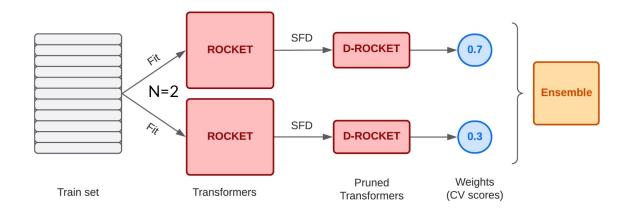




Explores a large set of kernels.



The resulting model is small.





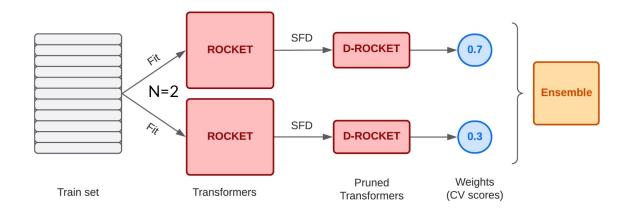
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Provides channel relevance.



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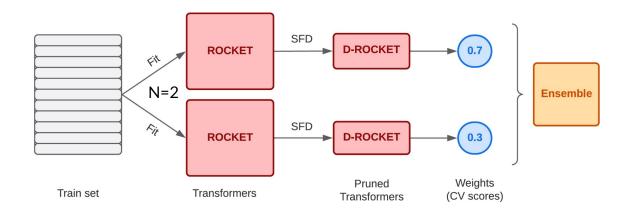
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Provides channel relevance.



Provides label probability! *





Explores a large set of kernels.



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Larger training time.

24 subject (16 train, 7 test) and **306 channels**. Classification task: is the subject observing a regular face or a scrambled face? *

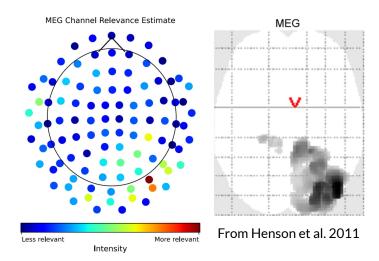
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Model	Train (%)	Test (%)
MiniRocket (20k kernles)	80.2±0.2	59.7±1.5
D-MiniRocket	72.2±2.9	60.8 ± 0.5
Arsenal	87.4±0.1	61.5 ± 0.4
D-Rocket Ensemble	78.6±0.3	$64.3{\pm}0.5$

D-Rocket Ensemble performs better

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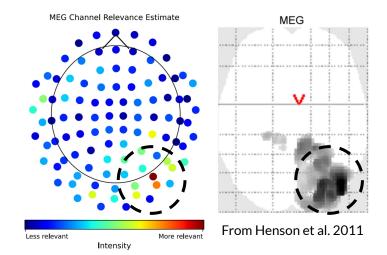
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We find the same relevant area

65 subject (LOSO CV) and **19 channels**. Classification task: is the subject a patient with **Alzheimer's Disease or a Healthy Control**?

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Type	${ m AD/CN}$ model	ACC	SENS	SPEC	PREC	$\mathbf{F1}$
	LightGBM	76.28%	76.08%	76.52%	79.67%	77.83%
ring	XGBoost	75.53%	76.08%	74.87%	78.55%	77.29%
engineering	CatBoost	75.39%	75.50%	75.25%	76.68%	77.05%
eng	SVM+PCA	73.75%	71.51%	76.46%	78.60%	74.89%
ure	PCA-kNN	72.52%	70.30%	75.19%	77.41%	73.69%
Feature	MLP *	73.69%	72.98%	74.81%	77.80%	75.31%
	DICE-net [18] *	83.28%	79.81%	87.94%	88.94%	84.12%
	EEGNet [15] *	41%	47.20%	37.67%	37.89%	42.04%
EEG	EEGNetSSVEP [28] *	51.46%	56.78%	45.39%	47.65%	51.82%
Raw E	DeepConvNet [23] *	54.21%	45.43%	57.59%	48.71%	47.01%
	ShallowConvNet [23] *	42.18%	46.50%	41.11%	49.74%	48.07%
	D-Rocket Ensemble	79.86%	78.89%	80.47%	74.89%	76.84%

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Not designed for EEG data!

Interpretability: EEG Channel Relevance Estimate Intensity Default th: 0.5 0.6 0.8

Experiments: EEG Dataset

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Hands-on Time: Notebook 5

Detach-ROCKET

ROCKET models

This is KEY!

Random Convolutional Kernel Transform (ROCKET)* is a transformation stage which can be applied to time-series data.

ROCKET

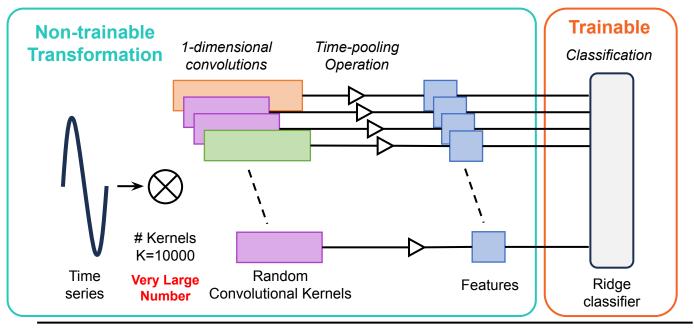
Kernels: Random Pooling: MAX + PPV # Features: 20000

MiniRocket

Kernels: Dictionary Pooling: PPV # Features: 10000

MultiRocket

Kernels: Dictionary
Pooling:
PPV+MPV+MIPV+LSPV
Features: 50000



Pruning ROCKET with SFD

We propose an algorithm to select the most relevant features called Sequential Feature Detachment (SFD)*.

