Karlsruher Institut für Technologie

Improving Human Activity Recognition Models by Learnable Sparse Wavelet Layer

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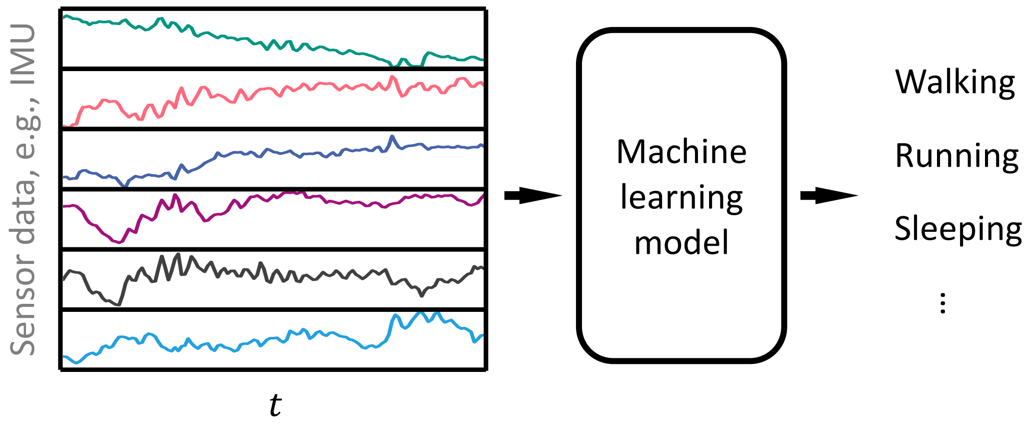
2022iSWC

Background

- Human activity recognition (HAR)



- State-of-the-art HAR models
  - DeepConvLSTM: conv + lstm
  - SA-HAR: conv + attention
  - MCNN: conv

Problems

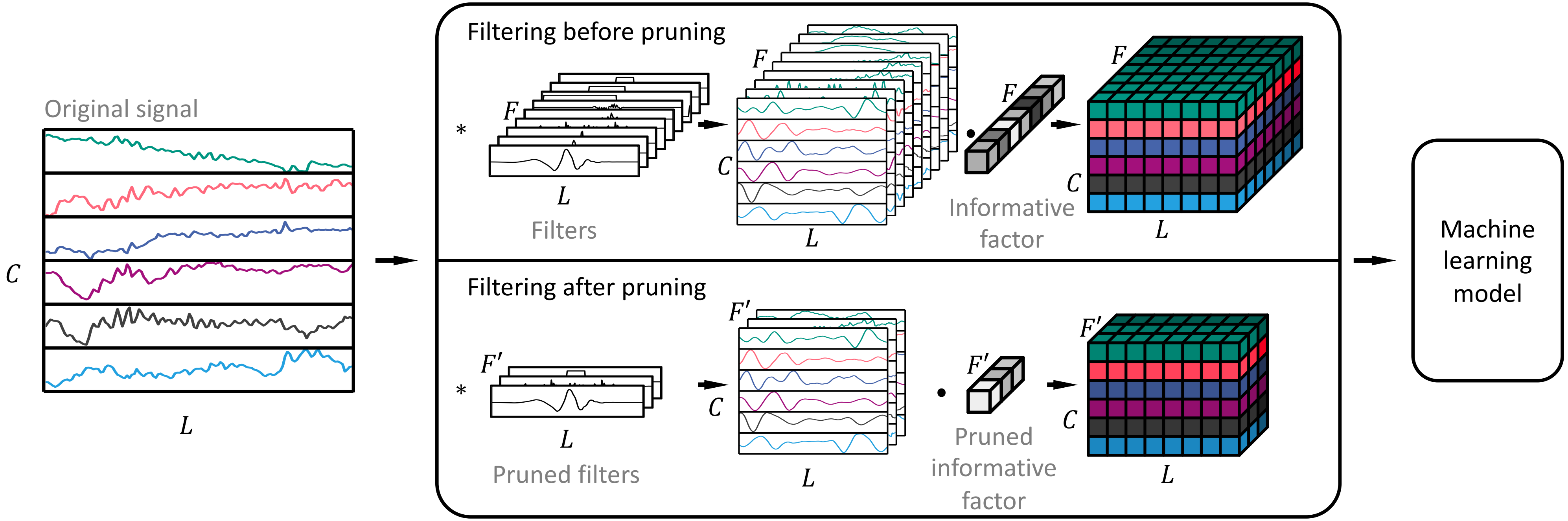
- Convolutional kernel
  - random initialization
  - training-data-oriented optimization
  - discouraged from exploring the search space
  - lost general properties for signal filtering
  - overfitting

Solution

- Wavelet
  - designed by expert knowledge
  - non-data driven
  - expressive
  - critical properties for filtering
    - bi-orthogonality
    - energy conservation
    - …
- Convolutional kernel
  - random initialization
  - training-data-oriented optimization
  - discouraged from exploring the search space
  - lost general properties for signal filtering
  - overfitting
- Hypothesis

  By combining wavelets with HAR models, the performance can be improved.

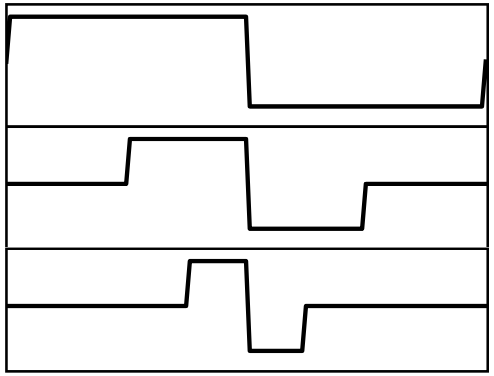
Learnable Sparse Wavelet Layer



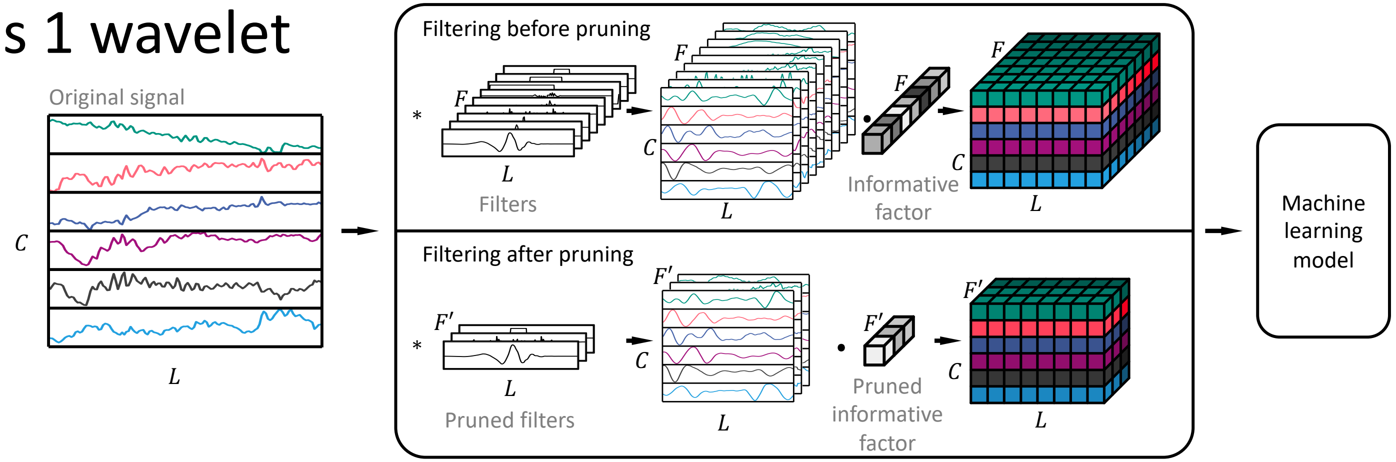
Pipline of the learnable sparse wavelet layer.

Learnable Sparse Wavelet Layer

Haar-wavelet



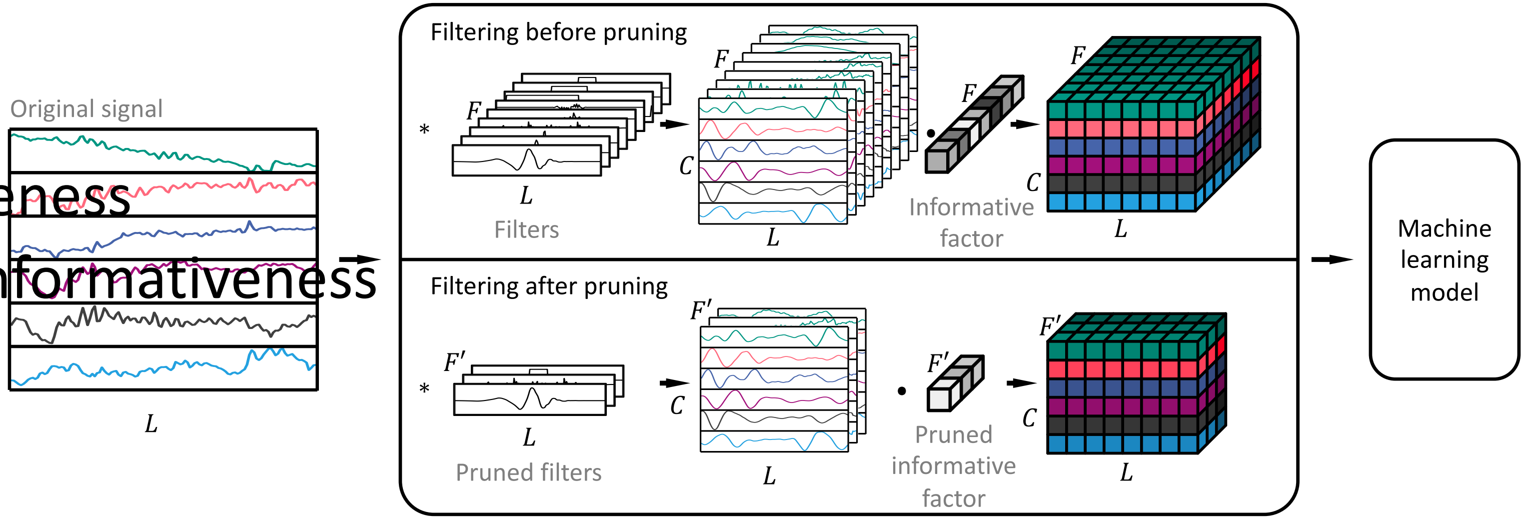
- Prepare mother wavelets
  - select all 127 discrete wavelets provided by PyWavelet[1]
  - re-sampling to the same length as sliding window in dataset
- Remove wavelets with high similarity (correlation)
  - e.g., Haar-wavelet = Daubechies 1 wavelet
- Temporal scaling factor
  - down sampling
  - zero padding
- Informativeness
  - filtered signal will be multiplied by the informative factor



[1] https://pywavelets.readthedocs.io/

Learnable Sparse Wavelet Layer

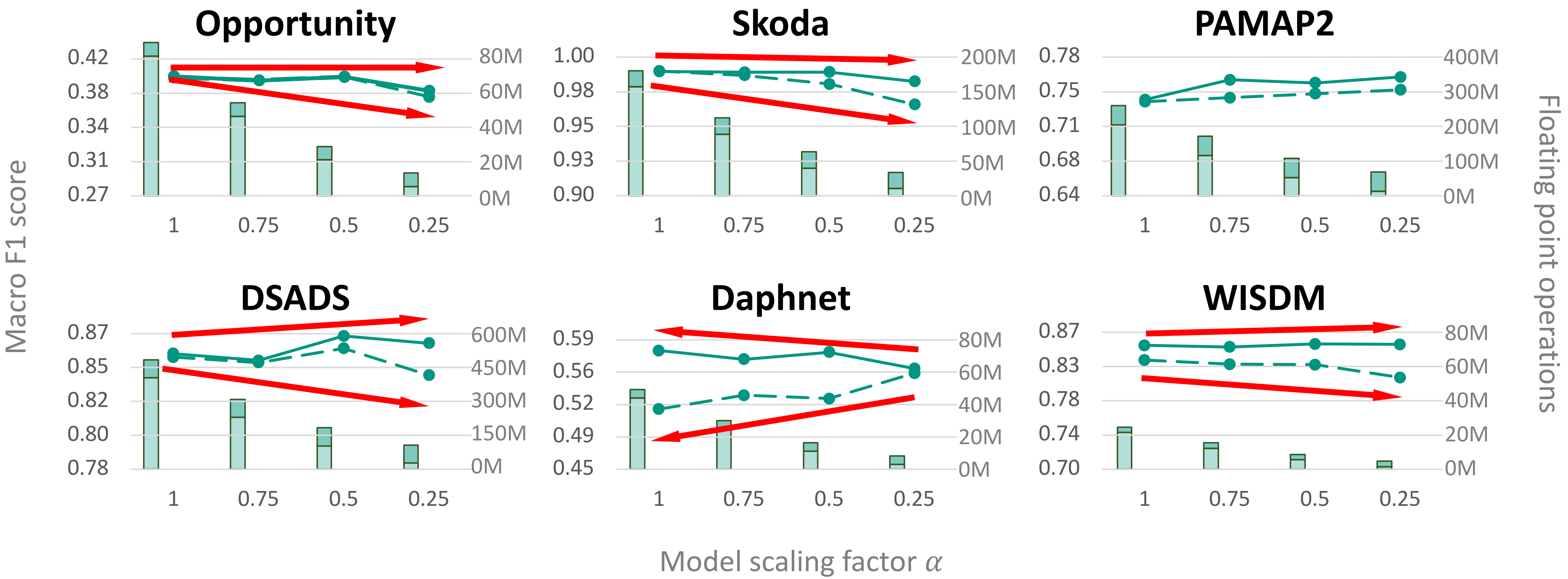
- Prepare mother wavelets
- Remove wavelets with high similarity (correlation)
- Temporal scaling factor
- Informativeness
- Filter pruning
  - ℓ_1 penalty on informativeness
  - remove filters with low informativeness
  - fine tuning



Experiment

- Benchmark datasets
  - Opportunity, Skoda, PAMAP2, DSADS, Daphnet, WISDM
- Baseline HAR models
  - DeepConvLSTM, SA-HAR, MCNN
- Model size scaling
  - 1, 0.75, 0.5, 0.25
- Setup
  - Baseline, Learnable Sparse Wavelet Layer (F=50), Learnable Wavelet Layer
- Metric
  - Macro F1 Score, Floating point operations

Result

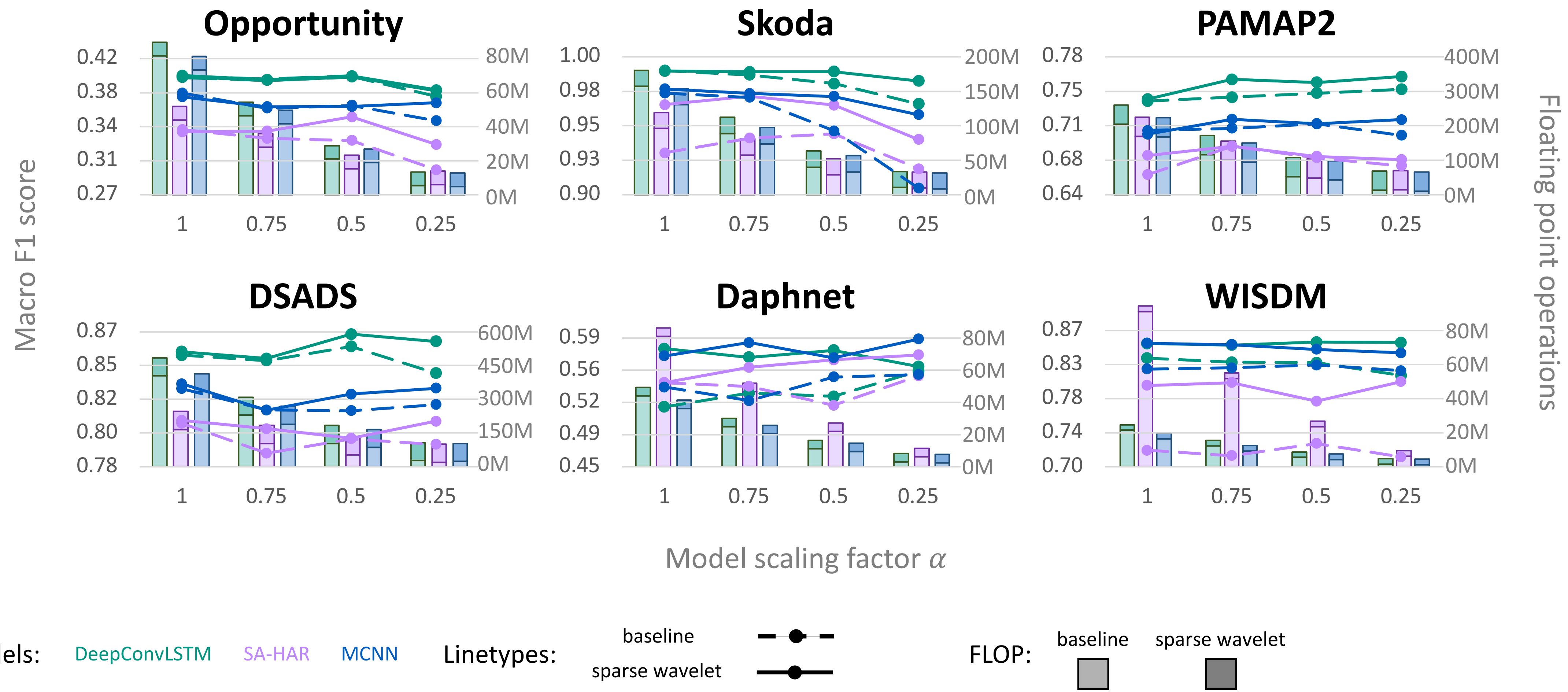


Models: DeepConvLSTM

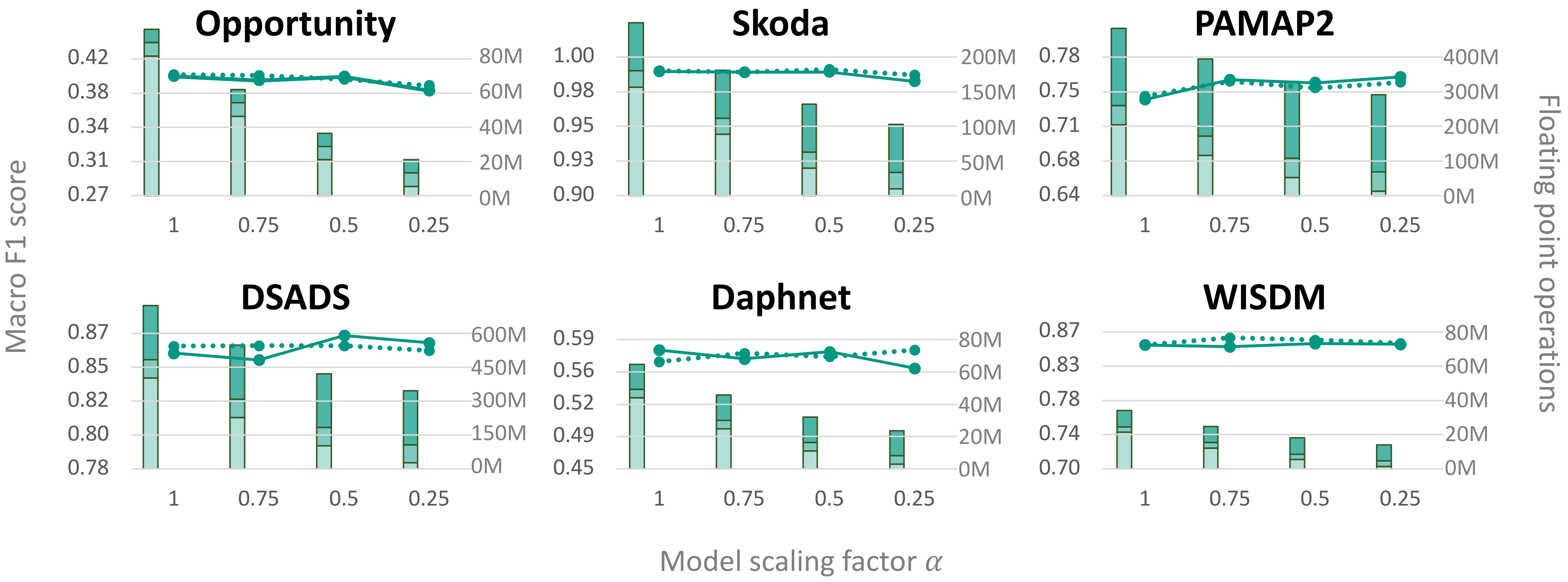
Linetypes: baseline, sparse wavelet

FLOP: baseline, sparse wavelet

Result


Opportunity
Skoda
PAMAP2
DSADS
Daphnet
WISDM
Macro F1 score
Floating point operations
Model scaling factor α
1
0.75
0.5
0.25
Models: DeepConvLSTM SA-HAR MCNN
Linetypes: baseline sparse wavelet
FLOP: baseline sparse wavelet

Result

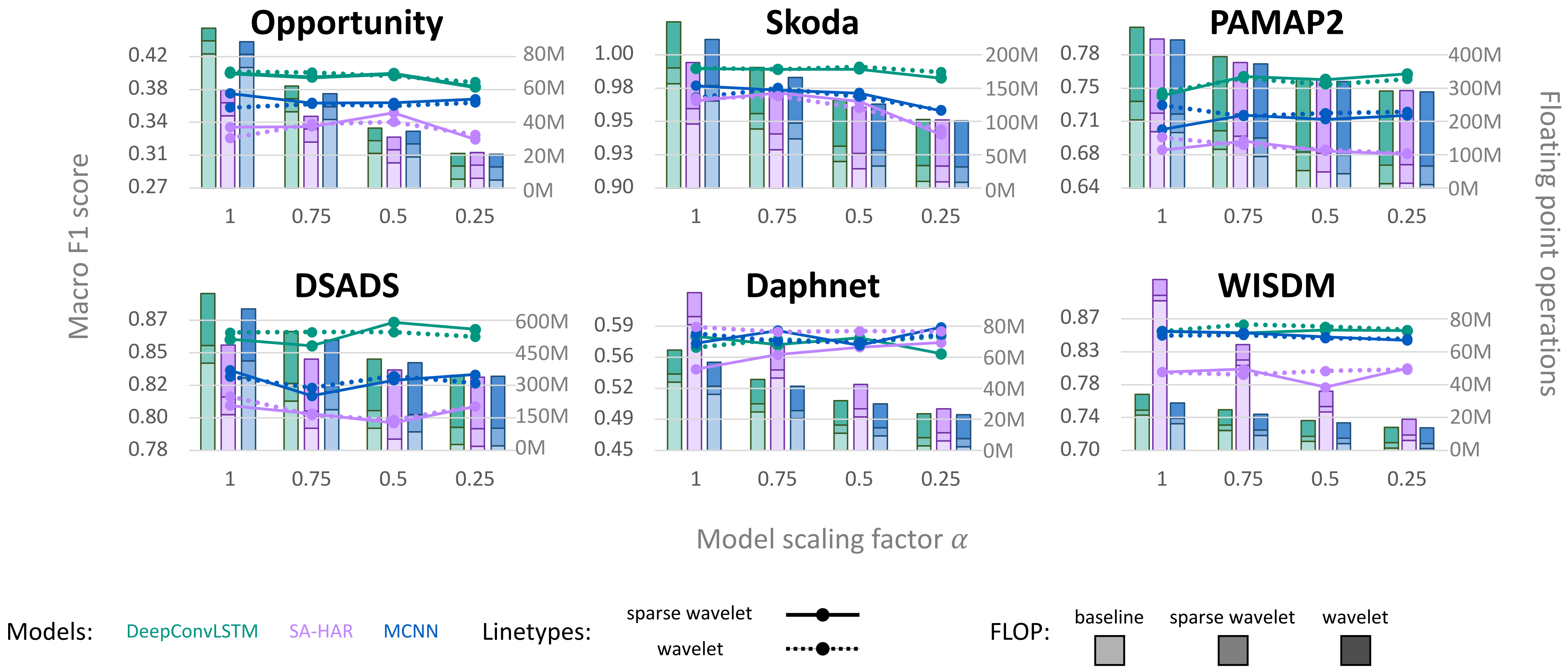


Models: DeepConvLSTM

Linetypes: sparse wavelet; wavelet

FLOP: baseline; sparse wavelet; wavelet

Result


Opportunity
Skoda
PAMAP2
DSADS
Daphnet
WISDM
Macro F1 score
Floating point operations
Model scaling factor α
0.42
0.38
0.34
0.31
0.27
80M
60M
40M
20M
0M
1
0.75
0.5
0.25
1.00
0.98
0.95
0.93
0.90
200M
150M
100M
50M
0.78
0.75
0.71
0.68
0.64
400M
300M
200M
100M
0.87
0.85
0.82
0.80
0.78
600M
450M
300M
150M
0.59
0.56
0.52
0.49
0.45
0.87
0.83
0.78
0.74
0.70
Models: DeepConvLSTM SA-HAR MCNN
Linetypes: sparse wavelet wavelet
FLOP: baseline sparse wavelet wavelet

Discussion

- The learnable sparse wavelet layer
  - improves the overall performance of the HAR models
  - mitigates the overfitting of HAR models with large size
  - compensates the feature extraction of HAR models with small size
- The improvement is more significant when the model is smaller
  - suitable for portable and wearable devices

Thank you for your attention