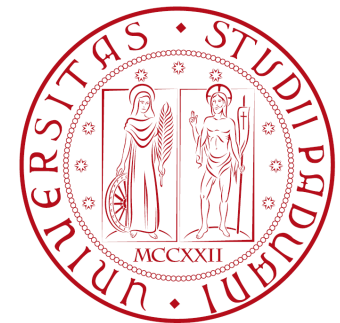


Semi-Supervised Autoencoder for Human Activity Recognition

Human Data Analytics

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- Problem Description
- Data Pre-Processing
- Conv1D NN
- Inception Style NN
- Semi-Supervised Autoencoder
- Conclusions

Human Activity Recognition (HAR):

Classification of Human Activity such as Running and Walking from sensors or videos

Sensor type HAR:

- Less difficult than video based (no need for cameras in the env.)
- Wide adoption of devices such as Smartphones and Wearables
- Privacy oriented (as mentioned no need for camera)
- Reduced costs of IMU sensor

Classification Model:

Deep Learning approach using raw data (no hand-crafted features)

Dataset composed by 4.5 hours of measurements in 9 axis from 16 individuals:

- Accelerometer (3 axis)
- Gyroscope (3 axis)
- Magnetometer (3 axis)

Activities Tracked

- Standing
- Sitting
- Lying
- Walking
- Running
- Jumping
- Falling



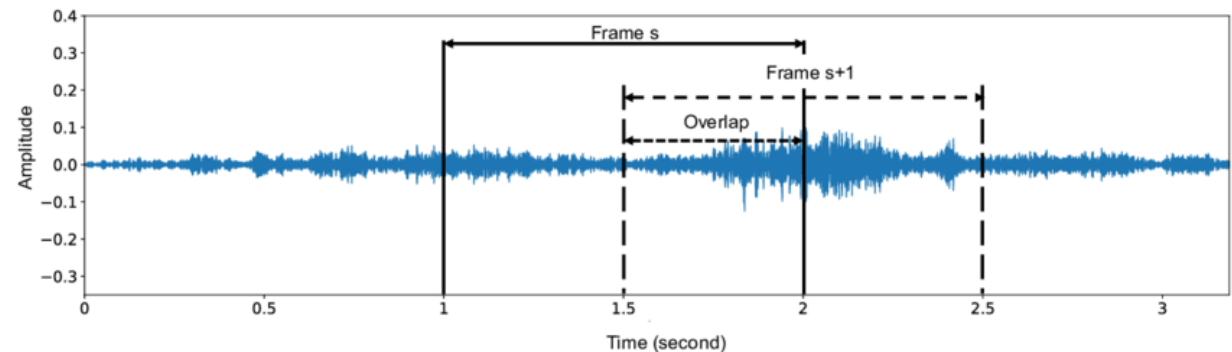
<https://www.xsens.com/products/mtw-awinda>

Difficulties with HAR data:

- Data taken from different individuals
- Every activity has different duration

Solution: Data framing

- Window size of 128
- Step of 8



https://www.researchgate.net/publication/333914934_End-to-End_Environmental_Sound_Classification_using_a_1D_Convolutional_Neural_Network

Data Framing

Magnetometer Drop



Data shape: 128x6

Not all labels have enough data

Data augmentation?

Unfortunately data augmentation
worsening the results in this case

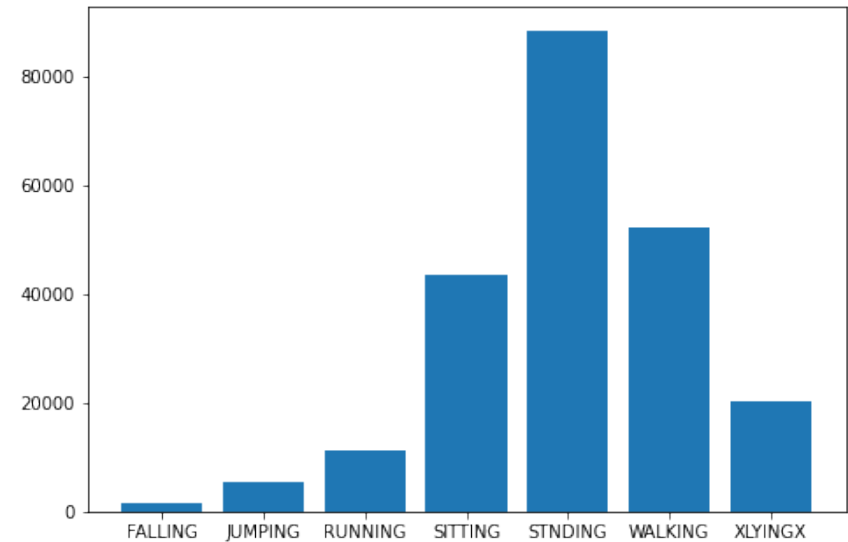
Data augmentation could add bias to
the data

Model learns from a wrong data distribution

Fortunately the following models are able to classify well also the less
represented labels

F1-score metric used to test the models

$$F1\text{-score} = 2 \frac{Precision \cdot Recall}{Precision + Recall}$$

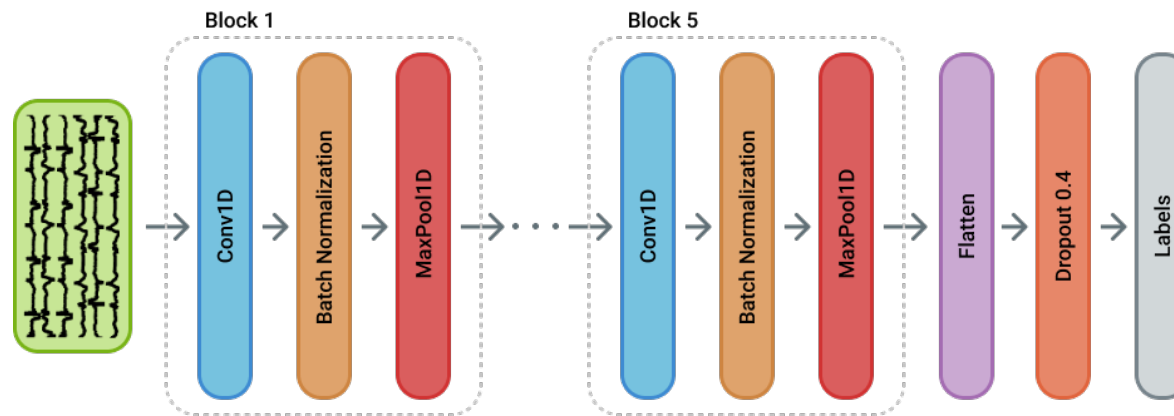


Conv1D NN Model

5 Convolutional layers each followed by batch norm and max pooling

Kernel Sizes: 9,7,5,3,3 **Stride:** 1 **Padding:** Same

Num Filters: 16,32,64,128,256

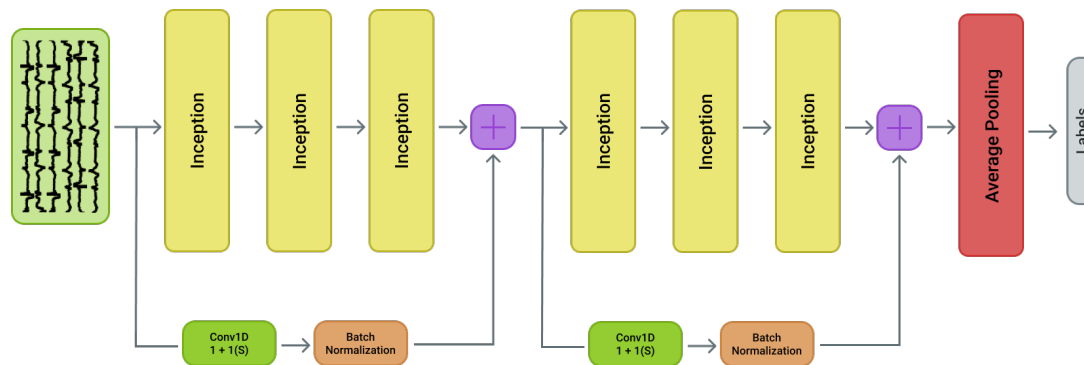


F1-Score	Falling	Jumping	Running	Sitting	Standing	Walking	Lying
Raw	0.92	0.96	0.99	0.98	0.99	0.99	0.98
DCT	0.77	0.87	0.98	0.84	0.92	0.98	0.77
Raw+DCT	0.86	0.94	0.99	0.93	0.97	0.99	0.90

Accuracy
98.83%
91%
96.2%

Inception Time NN

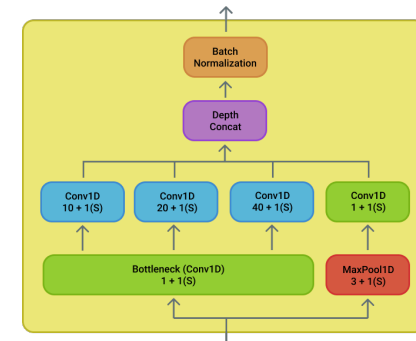
- Inspired by Inception Architecture from Computer Vision Domain
- Inception Network designed for Time-Series data
- Residual connection for every three inception blocks



Inception Block

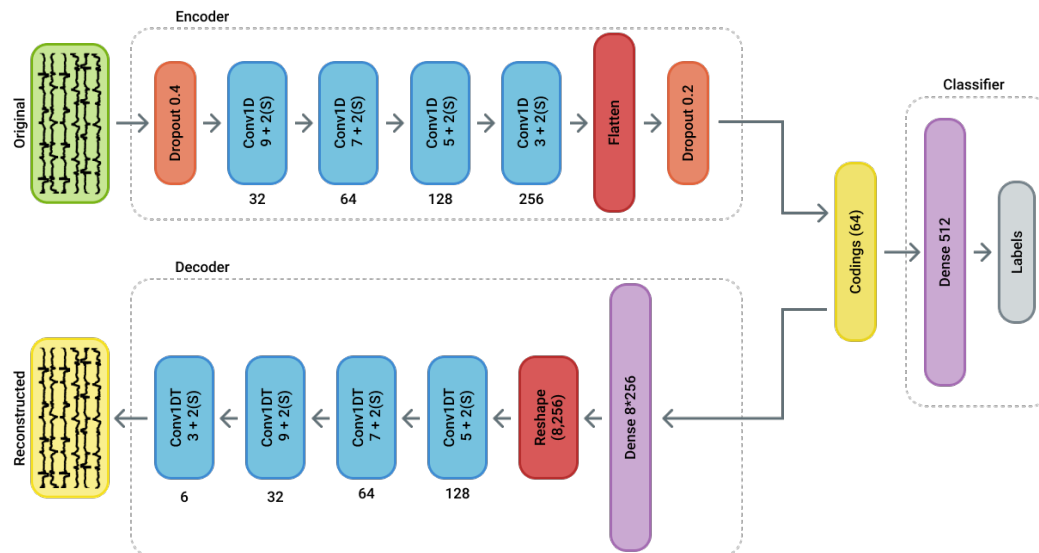
- Four parallel Conv1D branches
- Concatenation
- 1D convolution with kernel size 1 speeds up the training phase
- Each Conv1D has 32 kernels

F1-Score	Falling	Jumping	Running	Sitting	Standing	Walking	Lying	Accuracy
Raw	0.9	0.95	0.99	0.95	0.97	0.99	0.93	95.63%
DCT	0.65	0.85	0.97	0.89	0.94	0.98	0.8	92.26%
Raw+DCT	0.83	0.93	0.99	0.94	0.96	0.99	0.91	96.17%



Semi-Supervised AutoEncoder

- Composed by encoder, decoder and a classifier
- Learns from reconstruction error and classification error simultaneously
- Training time is similar to a classical AutoEncoder
- De-noising capability thanks to the dropout in the input of the encoder



Loss Function

$$J_{SSAE}(\theta) = \alpha J_{rec}(\theta) + \beta J_{class}(\theta)$$

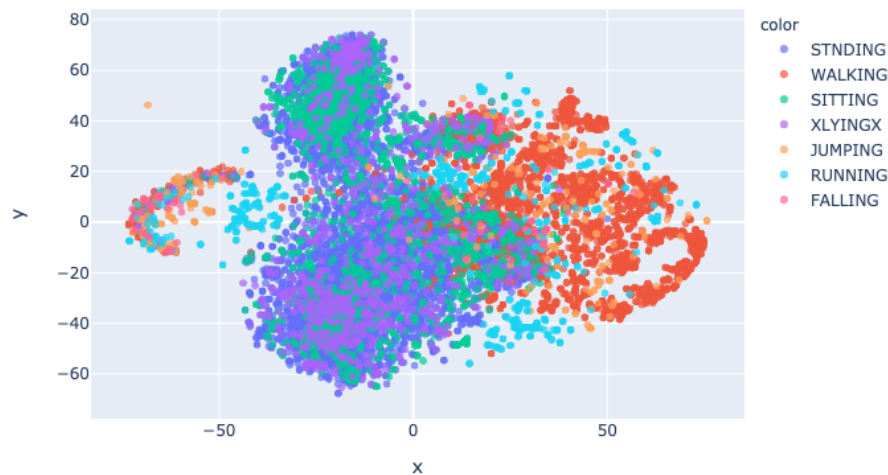
0.1

1.0

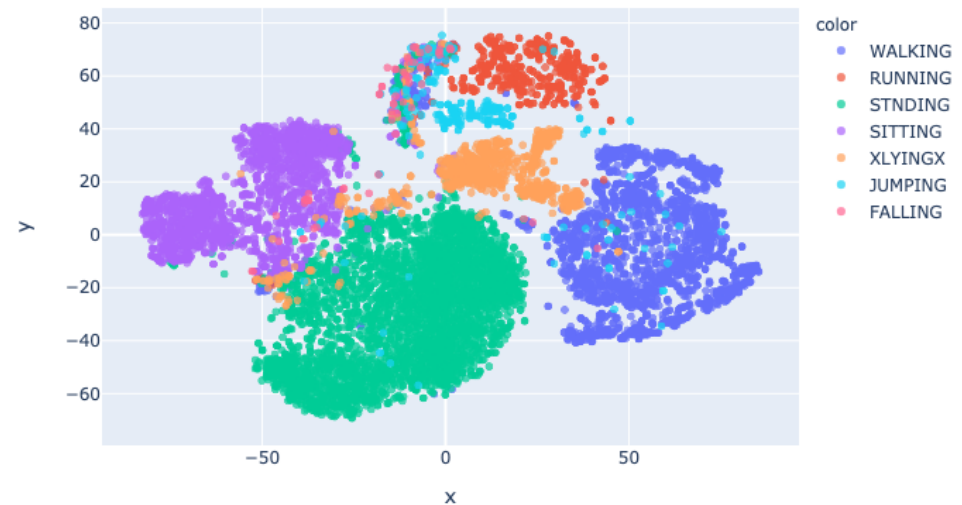
Advantages:

- Classification and Reconstruction in the same network
- Simple architecture but powerful and lightweight
- Good clusters in the latent space

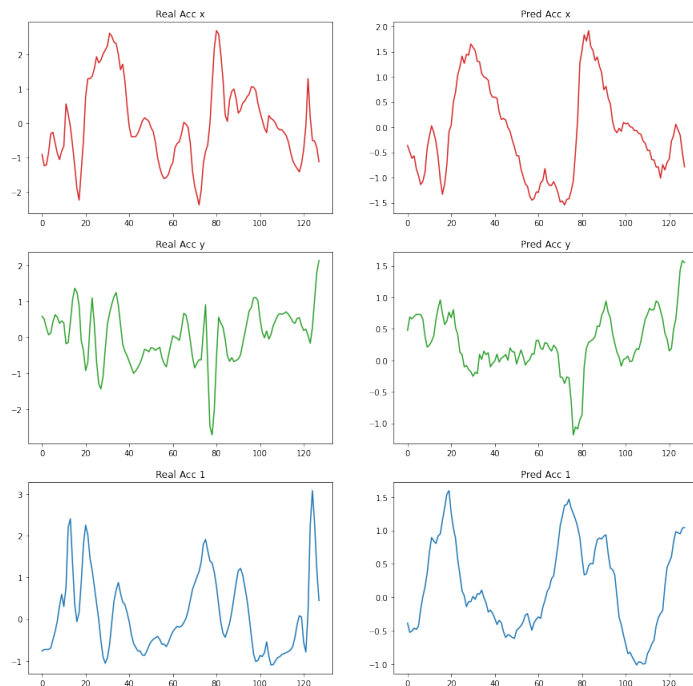
AE latent space



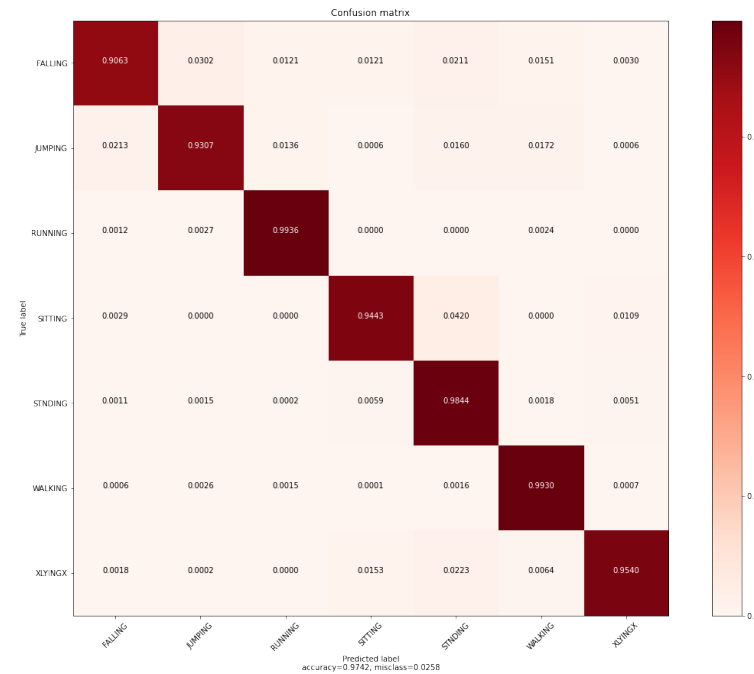
SSAE latent space



Reconstruction



Classification



F1-Score	Falling	Jumping	Running	Sitting	Standing	Walking	Lying
Raw	0.79	0.94	0.99	0.97	0.98	0.99	0.95
DCT	0.56	0.68	0.92	0.79	0.88	0.96	0.63
Raw+DCT	0.79	0.93	0.98	0.96	0.98	0.99	0.96

Accuracy
97.42%
85.47%
97.42%

- Semi-Supervised AutoEncoder achieves good classification and reconstruction results
- Classification results comparable with Conv1D model (best model)
- Could be used for supervised pre-training (few labeled samples can improve significantly the reconstruction error)
- For classification task of Human Activity is sufficient to use raw data

Future works

Implementation of Variational semi-supervised Autoencoders (VSSAE) for generative capability