

Improving Human Activity Recognition with Data Sources Integration

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Context & Motivation

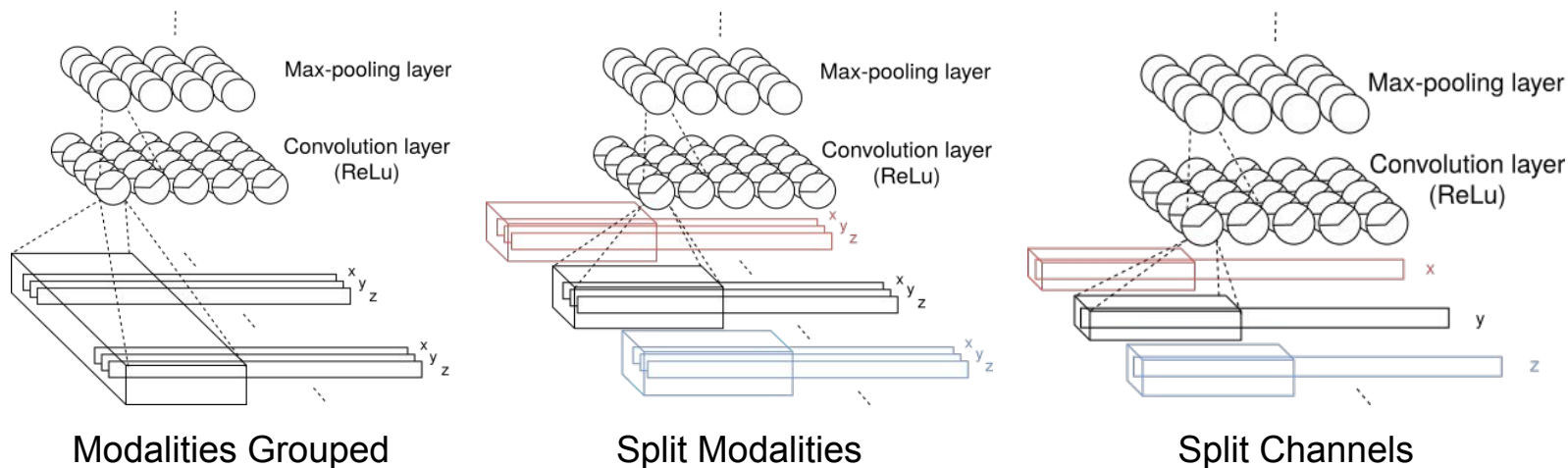
- How does the data generation step impact learning processes?
- How to deal with sensors deployments, Internet of Things environments, etc.?
- How to incorporate sensors deployment topology to improve data sources integration?
- How to come-up with similar insights as in [Foerster & al., Mantyjarvi & al., Reddy & al.] (without human expertise and heavy experimentation)?

F Foerster, M Smeja, J Fahrenberg - Computers in Human Behavior, 1999

Mantyjarvi, Jani, & al. *IEEE International Conference on Systems, Man and Cybernetics*. Vol. 2. IEEE, 2001

Reddy, S., Mun, M., Burke, J., Estrin, D., Hansen, M., Srivastava, M. *ACM Transactions on Sensor Networks (TOSN)* 6(2), 13, 2010

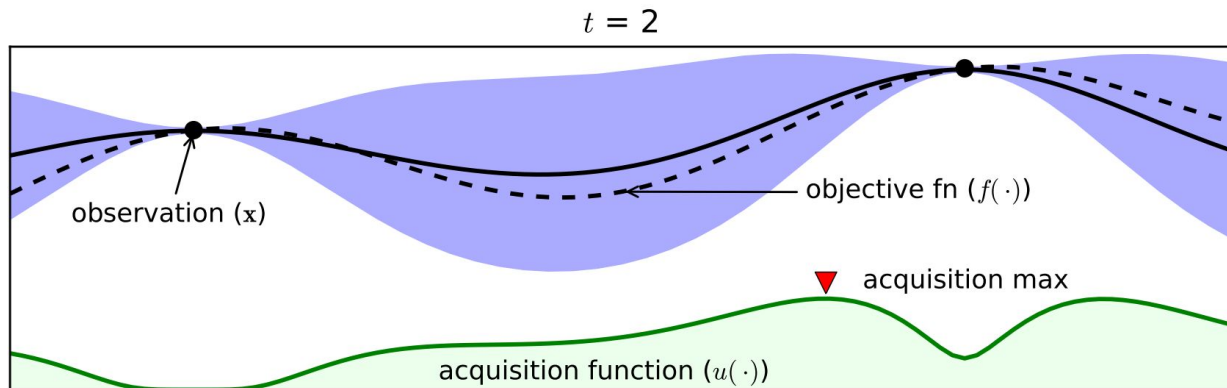
Features learning and fusion strategies



- Convolutional modes + hyperparameters instantiations define a neural architectures space;
- But, Exploration of the whole neural architectures space is unfeasible.

Optimal Exploration of the Neural Architectures Space

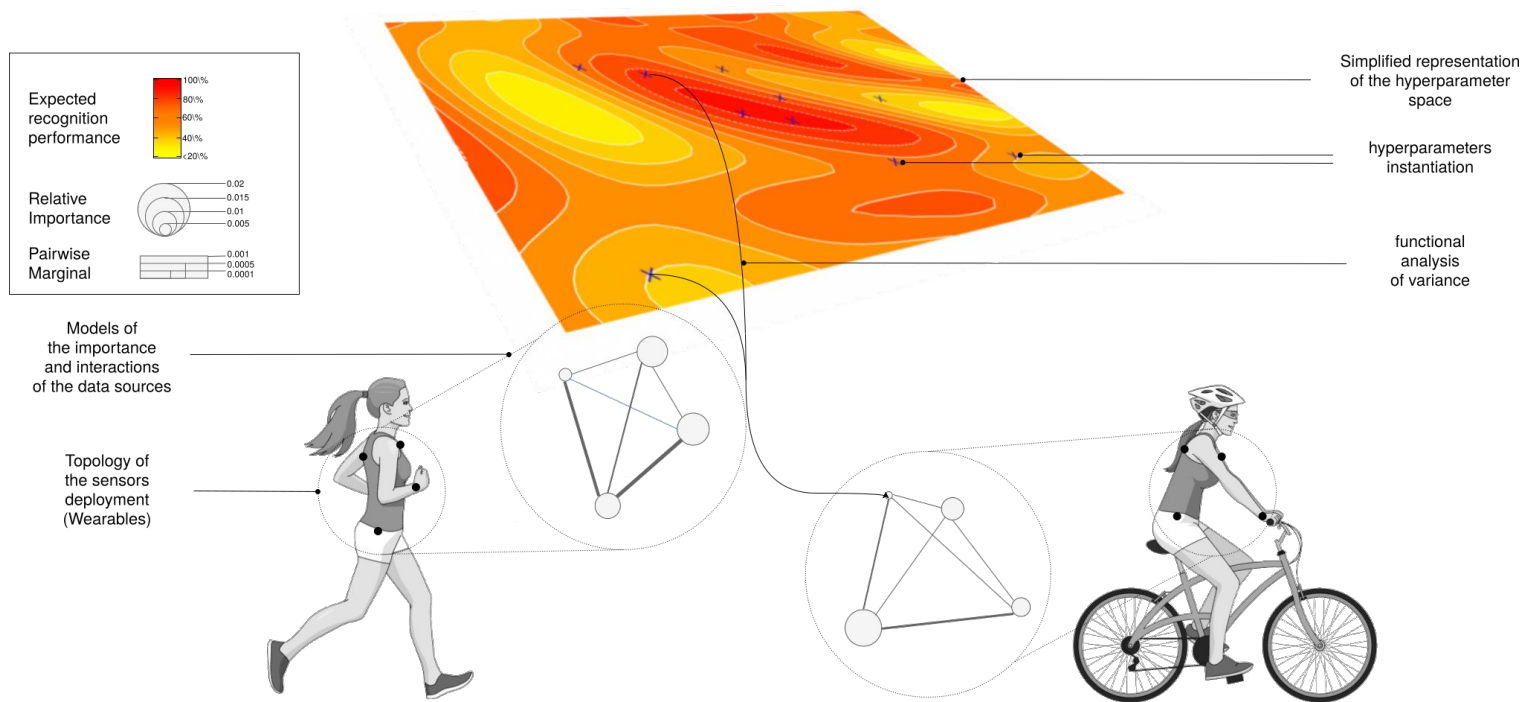
- Bayesian optimization based on Gaussian process surrogate model and expected improvement;
- Good trade-off between exploration and exploitation;



Data sources interactions & importances

- We seek the global influence of the hyperparameters;
- Functional analysis of variance (fANOVA) [Hutter & al. 2014];
- Decomposition of high-dimensional black-box functions into the contribution of their marginal components;
- In our case, the black-box function is the exploration strategy and the marginal components are the hyperparameters;

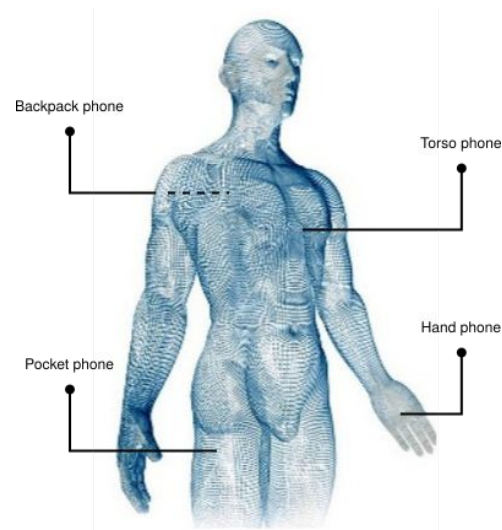
Proposed approach: recap



Experimental setting

- Sussex-Huawei Locomotion Dataset;
- Meta-segmented CV [Hammerla & al.];
- Averaged f1-score;
- Tensorflow, scikit-optimize, fANOVA;

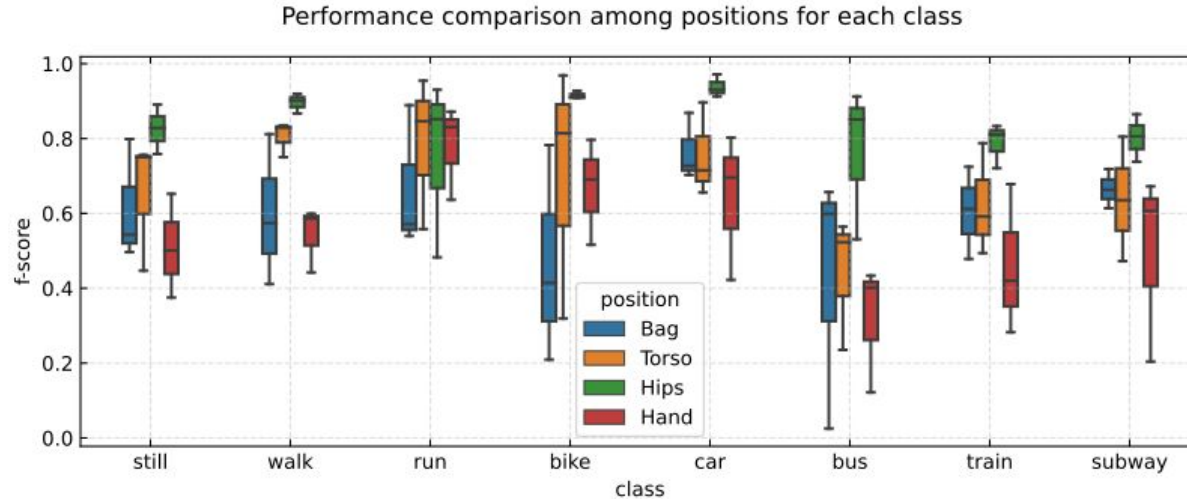
Hyperparam. (sym.)	low	high	prior
Kernel size 1 st layer ($ks_{1,mod}$)	9	15	-
Kernel size 2 nd layer ($ks_{2,mod}$)	9	15	-
Kernel size 3 rd layer ($ks_{3,mod}$)	9	12	-
Number of filters (nf_{mod})	16	28	-
Stride (s_{mod})	0.5	0.6	log
Learning rate (lr)	0.001	0.1	log
Dropout probability (p_d)	0.1	0.5	log
Number of units dense layer (n_u)	64	2048	-



Topology of the sensors deployment

NY Hammerla, T Plötz, in *UbiComp*, 2015

Qualitative evaluation of the interactions model (1)



Obtained model exhibits agreement with empirical results in the HAR literature, e.g. Foerster & al. and Mantyjarvi & al.

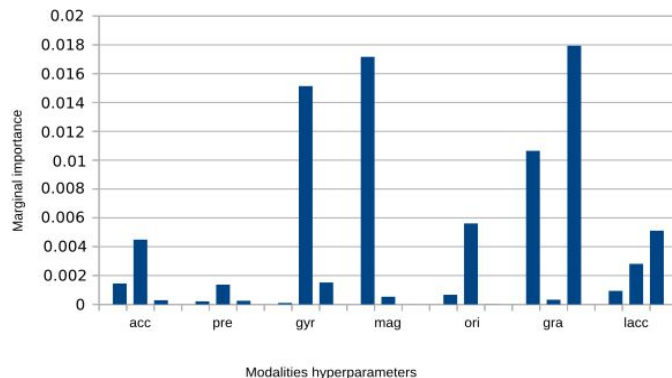
F Foerster, M Smeja, J Fahrenberg - Computers in Human Behavior, 1999

Mantyjarvi, Jani, & al. *IEEE International Conference on Systems, Man and Cybernetics*. Vol. 2. IEEE, 2001.

Qualitative evaluation of the interactions model (2)

Hyperparam.	Pairwise marginal ($\times 10^{-4}$)
$(k_{s_{gyr},2}, k_{s_{gra},2})$	9.2778
$(k_{s_{mag},1}, k_{s_{ori},2})$	7.0166
$(k_{s_{gyr},2}, k_{s_{ori},2})$	5.5122
$(k_{s_{acc},1}, k_{s_{mag},1})$	4.0382
$(k_{s_{pre},1}, k_{s_{gyr},3})$	2.3154
$(k_{s_{gyr},3}, k_{s_{mag},1})$	2.2472
$(k_{s_{mag},1}, k_{s_{ori},1})$	2.1216
$(k_{s_{pre},3}, k_{s_{gyr},2})$	1.76305

Most important pairwise marginals
of the kernel size hyperparameter



Individual marginal importance of
the kernel size hyperparameter

Conclusion & future work

- An original technique for making explicit the interactions among data sources;
- We leverage neural networks capabilities and recent advances in neural architecture search;
- Obtained models exhibits agreement with empirical results in the HAR literature;

- Data augmentation by replacing sensor measurements by random noise;
- Dropping connections that are not important according to the model;
- Adding a sensitivity-based regularization term: a modified term from [Tartaglione & al. 2018] that include, in addition to *parameter-output* sensitivity, an *input-parameter* sensitivity;