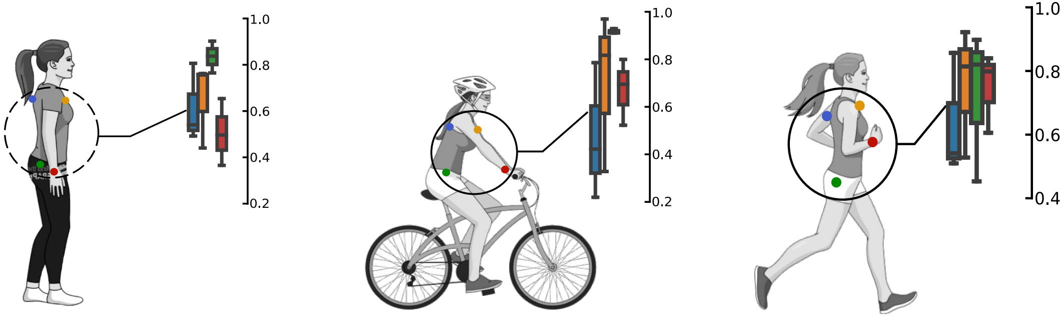
Data Generation Process Modeling for Activity Recognition



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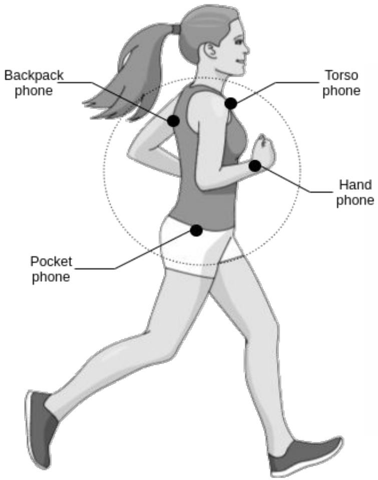
LIPN-UMR CNRS 7030, Univ. Sorbonne Paris Nord

ECML PKDD 2020

Motivation



Topology of the wearable sensors deployment in the Sussex Huawei locomotion transportation (SHL) dataset used in this work

accelerometer

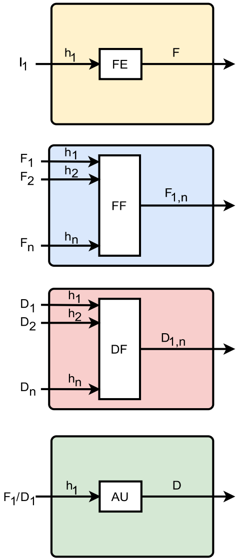
magnetometer

ambient pressure

gyroscope

...

Overview



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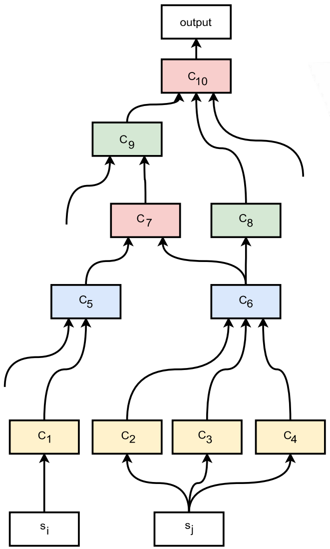

output
C10
C9
C7
C8
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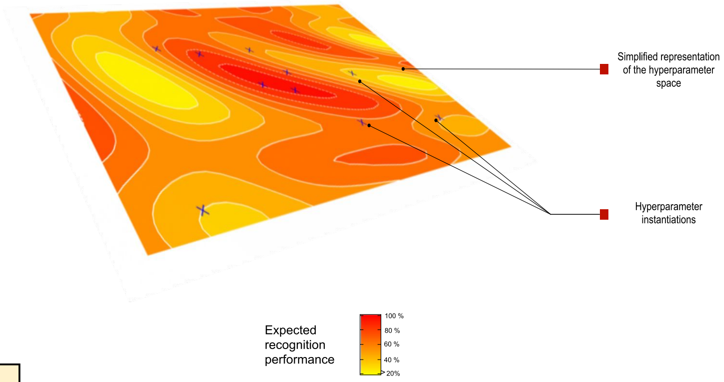
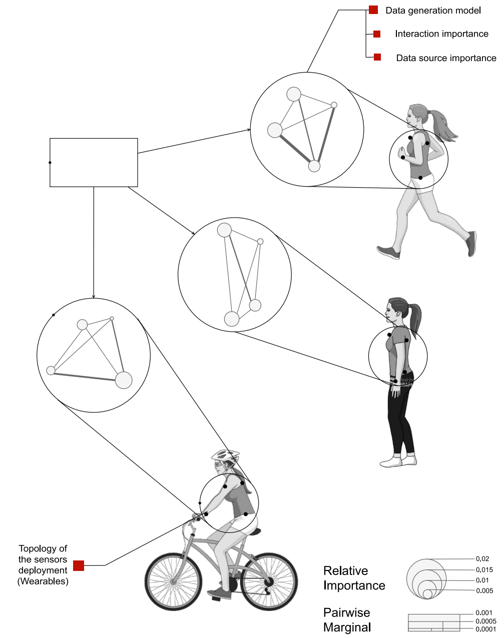
C4
si
sj



Simplified representation of the hyperparameter space
Hyperparameter instantiations
Expected recognition performance
100 %
80 %
60 %
40 %
20%



Data generation model
Interaction importance
Data source importance
Topology of the sensors deployment (Wearables)
Relative Importance
0,02
0,015
0,01
0,005
Pairwise Marginal
0.001
0.0005
0.0001

Contributions

- Evaluation on the **Sussex-Huawei locomotion dataset** featuring a sensor-rich environment in real-life settings;
- **Comprehensive comparative analysis** using 8 exploration strategies on 4 different representative related datasets;
- **Improvement of recognition performances** accompanied by a **substantial reduction of required learning examples**;

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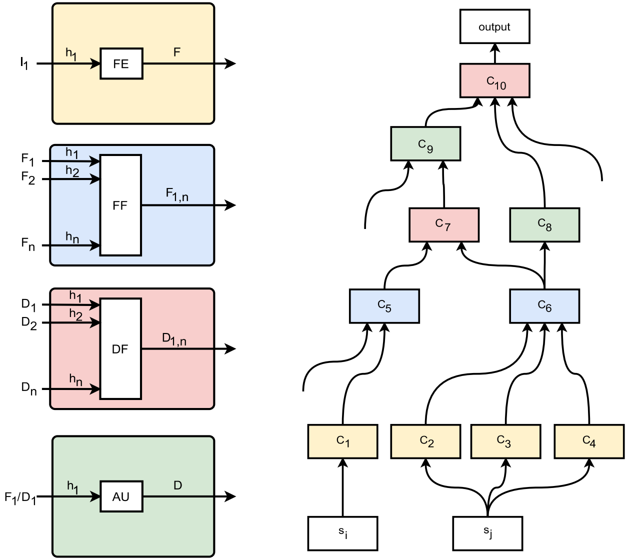
Proposed Approach

- Multimodal Architectures
- Architecture Space Exploration
- Variance-Based Importance Estimation

Multimodal Architectures

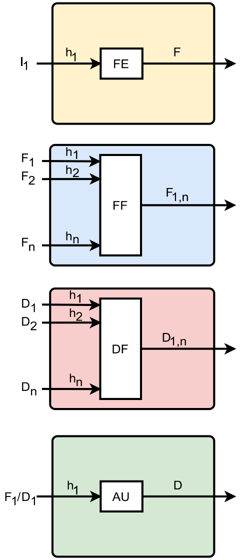


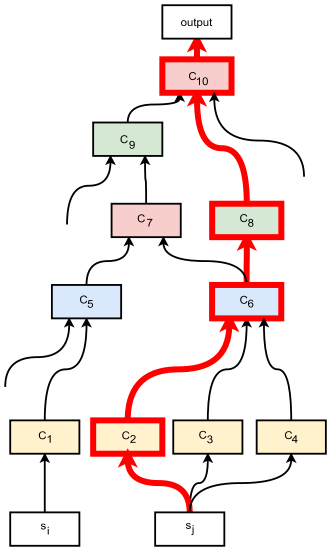
Four types of architectural components [Atrey et al., 2010]:
- feature extraction (FE);
- feature fusion (FF);
- decision fusion (DF);
- analysis unit (AU)

We associate a hyperparameter h_u^v with every edge in the directed graph that connects two components C_u and C_v.

PK Atrey, MA Hossain, A El Saddik, MS Kankanhalli - Multimedia systems, 2010

Multimodal Architectures





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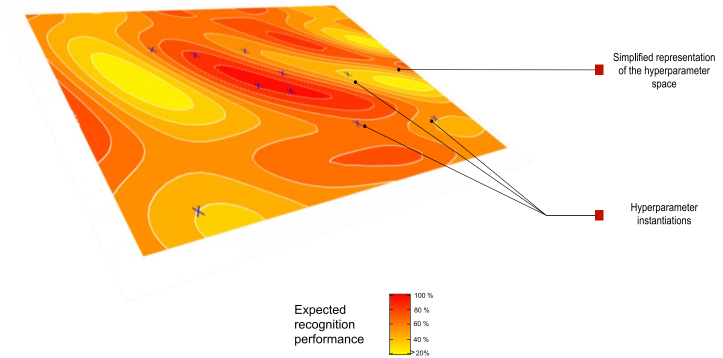
We associate a hyperparameter h_u^v with every edge in the directed graph that connects two components C_u and C_v.

The global impact of a set of hyperparameters (controlling the impact of s_j) on the architecture's performances represents the impact of s_j

PK Atrey, MA Hossain, A El Saddik, MS Kankanhalli - Multimedia systems, 2010

Architecture Space Exploration



Exploration is determined by three aspects:

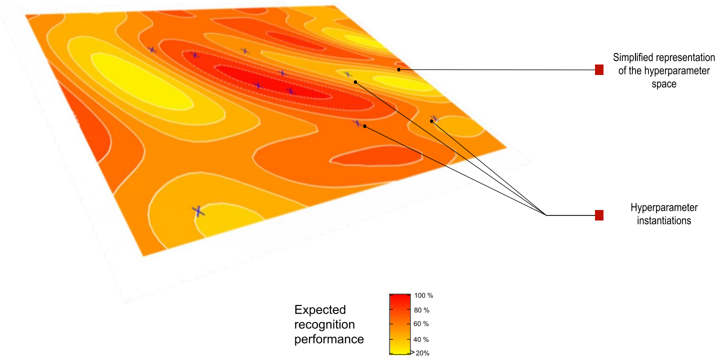
- search space;
- search strategy;
- performance estimation strategy.

The exploration strategy tries to find an architecture k^* that minimizes the validation loss ν_{k^*}.

Given an exploration budget B, the exploration strategy yields a series of validation losses $\nu_1, \ldots, \nu_B$

Elsken T, Metzen JH, Hutter F. - JMLR, 2019

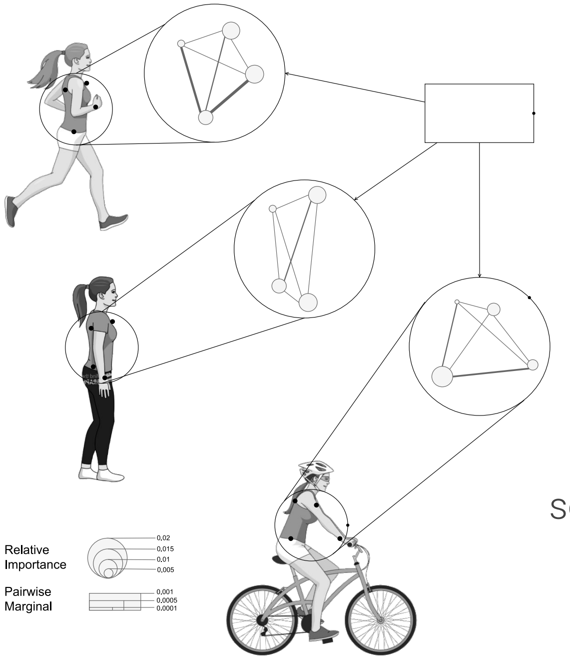
Architecture Space Exploration



search strategies:

- **Exhaustive search**
  - random search; grid search;
- **Heuristic search**
  - naive evolution; anneal; hyperband;
- **Sequential model-based**
  - BOHB; TPE; GP tuner;

Variance-Based Importance Estimation



Let $\mathcal{V} = \{\nu_1, \ldots, \nu_B\}$ be a set of validation losses.

To estimate the importance of each individual data source, we decompose the non-linear relation f described by $\mathcal{V}$ as follows:

$$f(\mathcal{S}, y) = \mu_0^y + \textstyle\sum_{i=1}^{M} \mu_i^y(s_i) + \sum_{i \neq j} \mu_{ij}^y(s_i, s_j) + \cdots + \mu_{1\ldots M}^y(s_i, \ldots, s_M)$$

set of M data sources

human activity

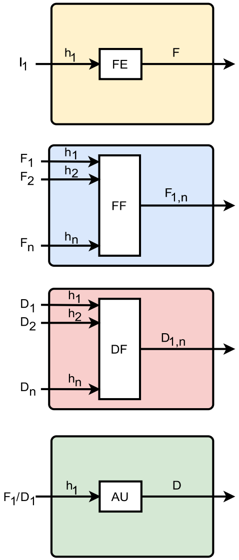
first-order effects

second-order effects

M th-order effects

Hoeffding, Wassily - The annals of mathematical statistics, 1948
H Hoos, K Leyton-Brown - ICML, 2014

Recap’



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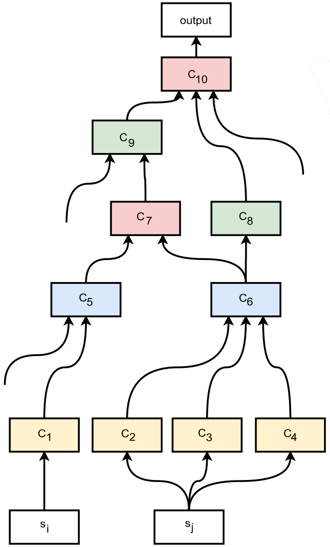

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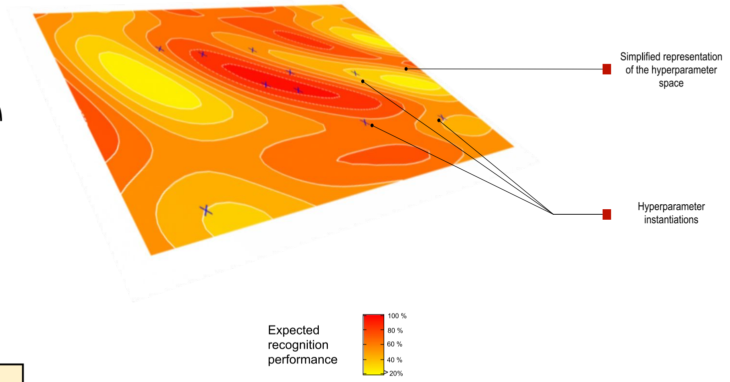

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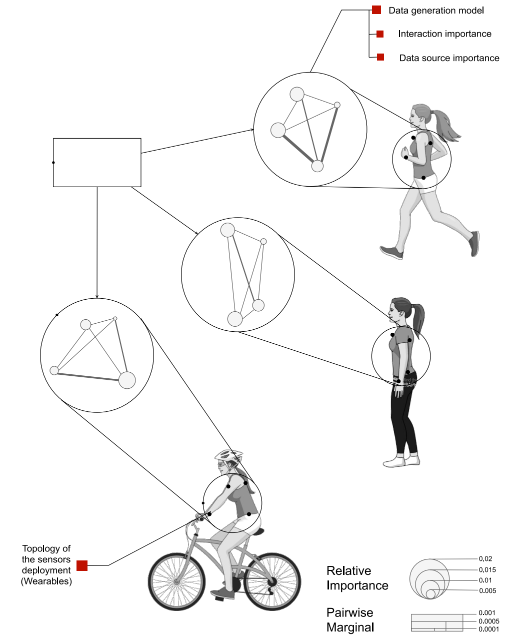

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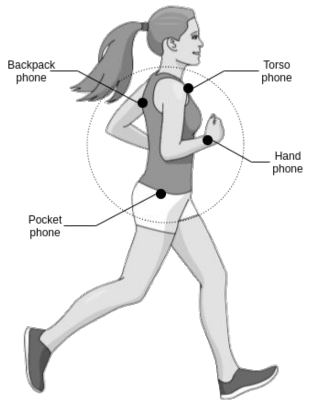
Experiments

Experimental Setup

- Datasets:
  - Sussex-Huawei locomotion (SHL) dataset [Gjoreski et al., 2018];
  - USC-HAD; US-TMD; HTC-TMD
- Architectural components:
  - Stacking of Conv1d/ReLU/MaxPool blocks (Tensorflow);
- Architecture space exploration:
  - Microsoft Neural Network Intelligence (NNI);
- Architectures evaluation:
  - Meta-segmented CV [Hammerla et al., 2015];
  - Averaged f1-score [Forman et al., 2010];
- Variance-based importance estimation
  - functional analysis of variance [Hoos et al., 2014]



Topology of the wearable sensors deployment in the Sussex Huawei locomotion transportation (SHL) dataset used in this work

H Gjoreski et al. - IEEE Access 6, 2018
https://github.com/microsoft/nni
NY Hammerla, T Plötz - UbiComp, 2015
G Forman, M Scholz - Acm Sigkdd Explorations Newsletter, 2010
H Hoos, K Leyton-Brown - ICML, 2014

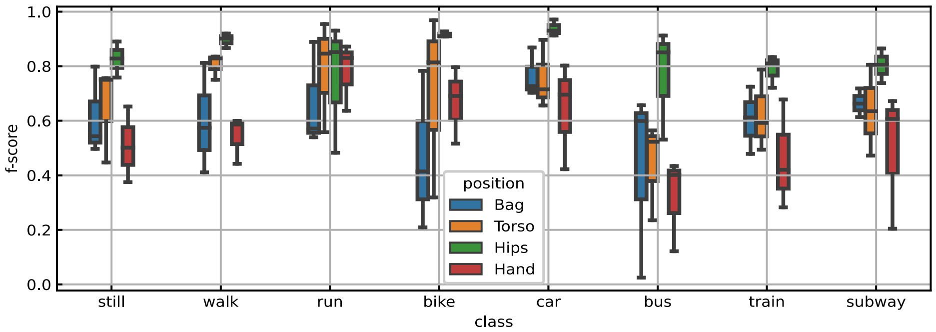
Derived Data Generation Model

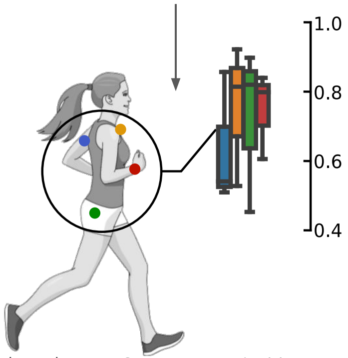
Impact of the space exploration strategies

Exploration strategy	Agreement	ν_k on avg.
Exhaustive search		
Random Search	0.156± 0.04	67.12%
Grid Search	**0.251±0.05**	66.78%
Heuristic search		
Naïve evolution	0.347±0.12	73.35%
Anneal	**0.481±0.05**	75.47%
Hyperband	0.395±0.08	74.2%
Sequential Model-Based		
BOHB	0.734±0.03	84.25%
TPE	0.645±0.1	83.87%
GP Tuner	**0.865±0.02**	84.95%

Derived Data Generation Model

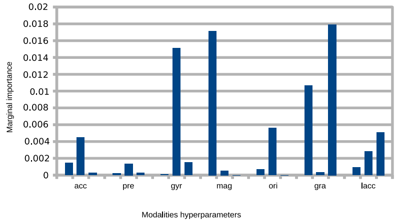
A closer look into the derived model





Hyperparam.	Interaction ($\times 10^{-4}$)
(ks^2_{gyr}, ks^2_{gra})	9.2778
(ks^1_{mag}, ks^2_{ori})	7.0166
(ks^2_{gyr}, ks^2_{ori})	5.5122
(ks^1_{acc}, ks^1_{mag})	4.0382
(ks^1_{pre}, ks^3_{gyr})	2.3154
(ks^3_{gyr}, ks^1_{mag})	2.2472

Most important pairwise marginals of the kernel size hyperparameter



Individual marginal importance of the kernel size hyperparameter

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

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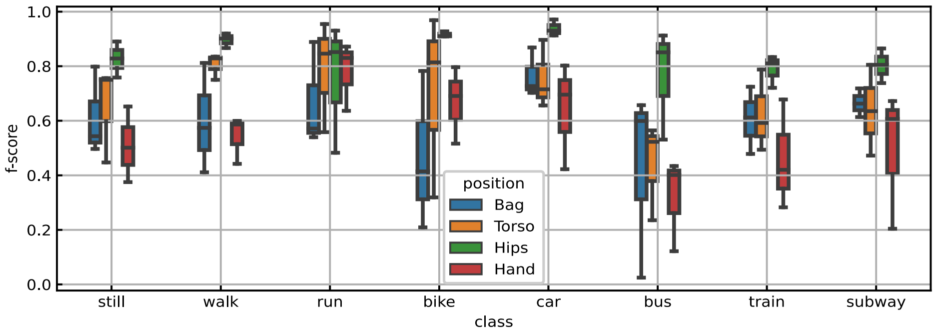

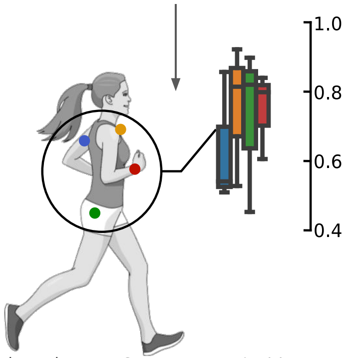

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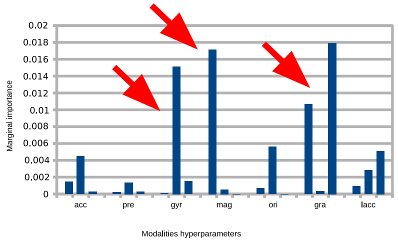

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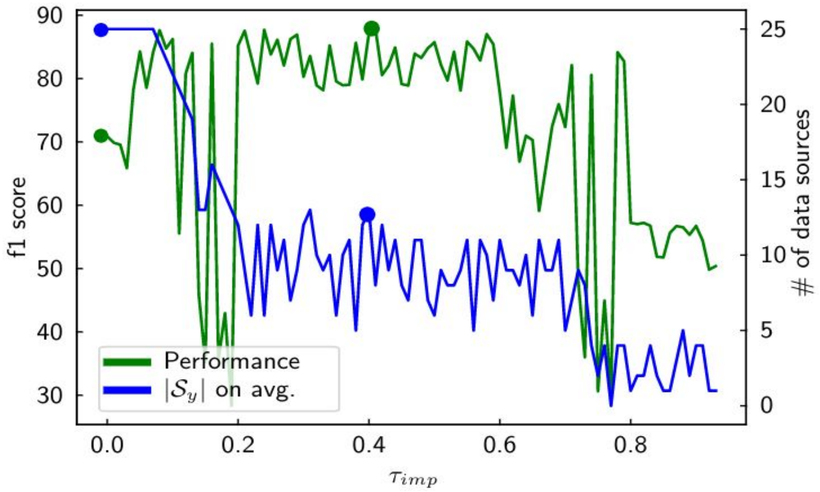
Effectiveness of the Data Generation Model

Dataset	Performances		
	wo-DGP	w-HExp	w-DGP
USC-HAD	72.1%	75.38%	89.33%
HTC-TMD	74.4%	77.16%	78.9%
US-TMD	71.32%	80.28%	83.64%
SHL	70.86 %	77.18%	88.7%



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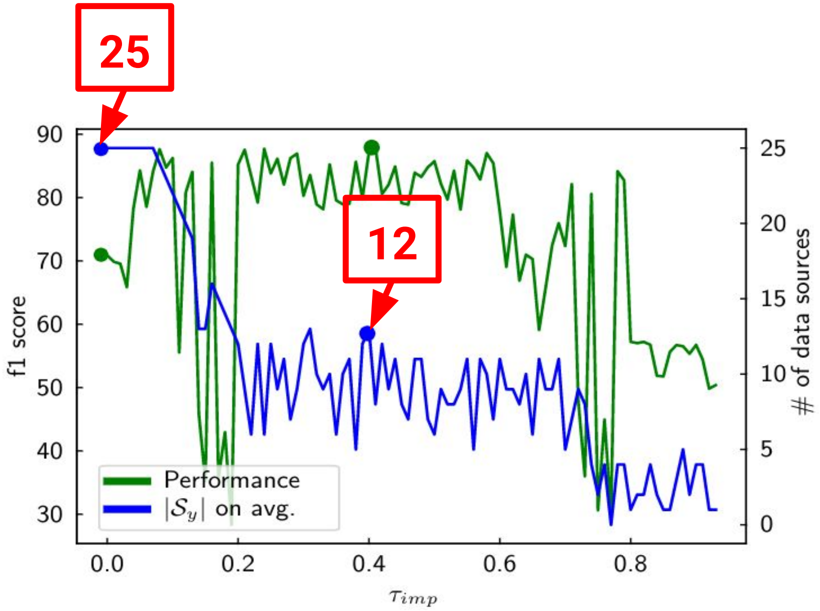

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