Generative models for human activity recognition

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Project goal

Aim

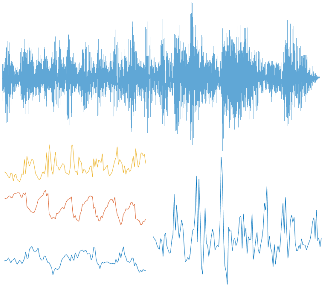
Classification model for complex-structured objects.

Problem

Initial object has no appropriate feature description.

Applications:

- image processing;
- signal classification;
- topic modelling;
- *time series analysis*.



Related work

1. Wang W. et al. Human activity recognition using smart phone embedded sensors: A Linear Dynamical Systems method. *Neural Networks (IJCNN), 2014 International Joint Conference on (pp. 1185-1190)*. IEEE.

2. Kwapisz J. R., Weiss G. M., Moore S. A. Activity recognition using cell phone accelerometers. *ACM SigKDD Explorations Newsletter*, 12(2), 74-82, 2011

3. Kuznetsov M. P., Ivkin N. P. Time series classification algorithm using combined feature description. *Journal of Machine Learning and Data Analysis*, 2015.

Problem Statement

Let: $s \in \mathcal{S}$ — complex structured object;
$y \in Y$ - class label;

Task

Suppose to be given the set of labeled data $\mathfrak{D} = \{(s_i, y_i)\}_{i=1}^m$.
Our goal is to determine function f^*, such that

$$f^* = \arg\min_f L(f, \mathfrak{D}),$$

where $L(\cdot, \cdot)$ is an error function and $f : \mathcal{S} \to Y$.

Approach

Suppose $f = g \circ h$, where

1. $h(s) : \mathcal{S} \to H \subset \mathbb{R}^n$ is map from $\mathcal{S}$ into feature space H;
2. $g(\boldsymbol{h}, \boldsymbol{\theta}) : H \to Y$ is parametric map (classification model).

Optimal parameters

$h(s)$

Choice of feature map $h(s)$ by

- prior (expert) knowledge;
- minimizing error functional.

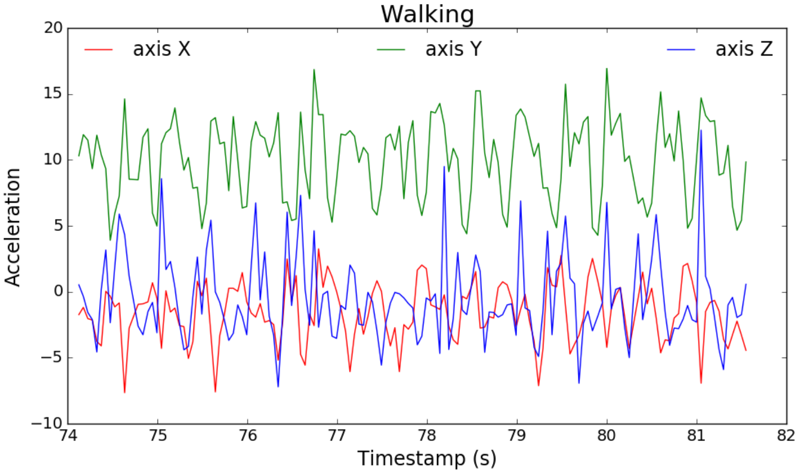
$g(\boldsymbol{h}, \theta)$

Classification for $\{(\boldsymbol{h}_i, y_i)\}_{i=1}^m$

$$\boldsymbol{\theta}^* = \arg\min_{\boldsymbol{\theta}} L(g, \boldsymbol{\theta}, \mathfrak{D}).$$

E.g.: $g(\mathbf{h}, \boldsymbol{\theta})$ - classification model;
$\boldsymbol{\theta}$ - model parameters;
$L(g, \boldsymbol{\theta}, \mathfrak{D})$ - classification error function.

Time series example



Expert functions

Prior knowledge about the objects could allow to choose the features.

Feature description

$\mathbf{h}_i = h(s_i) \in \mathbb{R}^{40}$ — different statistics:

- average acceleration;
- standard deviation;
- mean absolute deviation;
- ...

Autoregressive model

Data generation hypothesis

Time series $s = (x_1, \dots, x_T)$ is generated by autoregressive model

$$\hat{x}_t = w_0 + \sum_{j=1}^{n} w_j x_{t-j}.$$

Feature description

$$h(s_i) = \mathbf{w}^* = \arg \min_{\mathbf{w} \in \mathbb{R}^{n+1}} \sum_{j=n+1}^{T} \|x_j - \hat{x}_j\|^2.$$

Singular Spectrum Analysis (SSA)

Trajectory matrix for time series $s = (x_1, \dots, x_T)$:

$$\mathbf{X} = \begin{pmatrix} x_1 & x_2 & \dots & x_n \\ x_2 & x_3 & \dots & x_{n+1} \\ \dots & \dots & \dots & \dots \\ x_{T-n+1} & x_{T-n+2} & \dots & x_T \end{pmatrix}.$$

Feature description

$$h(s_i) = (\lambda_1, \dots, \lambda_n),$$

where $\{\lambda_i\}_{i=1}^{n}$ are eigenvalues of the matrix $\mathbf{X}^\mathsf{T}\mathbf{X}$, obtained by SVD decomposition

$$\mathbf{X}^\mathsf{T}\mathbf{X} = \mathbf{V} \cdot \mathrm{diag}(\lambda_1, \dots, \lambda_n) \cdot \mathbf{V}^\mathsf{T}.$$

(?!) Splines

Data

WISDM[1]

Activity	# objects
Standing	229(5.3%)
Walking	1917(44.4%)
Upstairs	466(10.8%)
Sitting	277(6.4%)
Jogging	1075(24.9%)
Downstairs	357(8.3%)
Total	4321

USC-HAD[2]

Activity	# objects
Standing	1167(8.6%)
Elevator-up	764(5.6%)
Walking-forward	1874(13.8%)
Sitting	1294(9.5%)
Walking-down	951(7%)
Sleeping	1860(13.7%)
Elevator-down	763(5.6%)
Walking-upstairs	1018(7.4%)
Jumping	495(3.6%)
Walking-right	1305(9.6%)
Walking-left	1280(9.4%)
Running	849(6.2%)
Total	13620

[1] http://www.cis.fordham.edu/wisdm/

[2] http://sipi.usc.edu/HAD/

Experiment

- datasets: WISDM, USC-HAD;
- feature extraction methods: expert functions, autoregressive models, singular spectral analysis, splines;
- classification models: logistic regression, support vector machine, random forest;
- tuning parameters: cross-validation;
- quality measure: accuracy score.

Results

	Expert	AutoReg	SSA	Splines
Log-Reg	0.668	0.651	0.637	0.415
SVM	0.797	0.655	0.822	0.740
RF	0.871	0.703	0.840	0.736

Feature union

Conclusion

Done

- different approaches to classification of complex-structured objects were studied
- the results of experiments on human activities datasets outperform many previous methods
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Future work

- new approaches to feature extraction (e.g. modified splines)
- implementing of structured learning methods