Pattern matching for multivariate time series forecasting

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Contents

Introduction

Explanation of the aim

For each time series i of a set I of time series, we have a time series at a set of times $\mathbf{t}_i = \{t_{i1}, \ldots, t_n\}$:

$$x_i(\mathbf{t}_i) = x_i(t_{i1}), \ldots, x_i(t_n)$$

So the objective is to produce predictions over a range of times $\mathbf{t}_h = \{t_{n+1}, \ldots, t_{n+h}\}$.

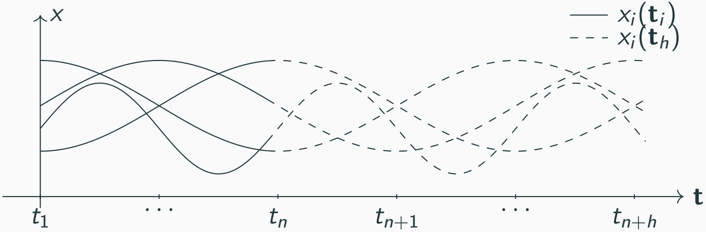


Figure 1: Representation of our problem

Weigthed Nearest Neighbors (WNN) for multivariate time series(WNN_{multi})

Weighted Nearest Neighbors (WNN) [3]

With nearest neighbor search, the objective is to predict the sequence of a curve up to the horizon h. Two hyperparameters need to be set: w and k.

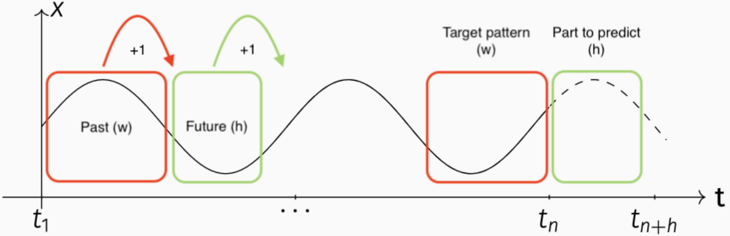
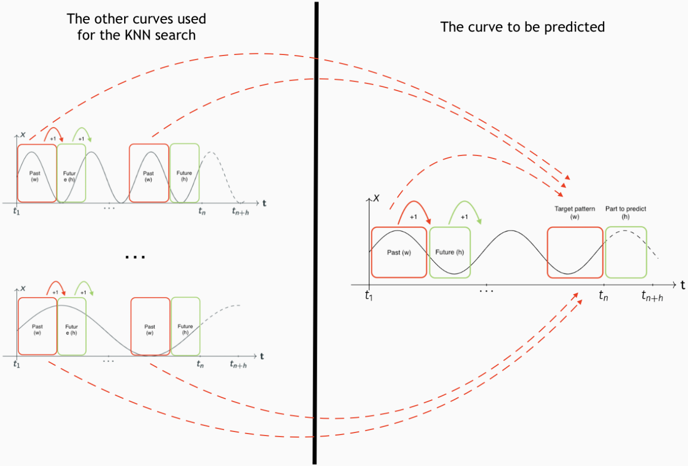


Figure 2: Past/future split using a sliding window.

Weigthed Nearest Neighbors (WNN) for multivariate time series(WNN_{multi})

In our context, we propose to use information from several curves to predict a particular curve.



Weigthed Nearest Neighbors (WNN) for multivariate time series(WNN_{multi})

WNN_{multi} **algorithm**:

- Splitting the curves to obtain 2 sets: E_p (past) and E_f (future)
- For each curve :
    - Euclidean distance between the target pattern and the other patterns in E_p.
    - Selection of k patterns.
    - Calculation of α_i weights (based on distances).
    - Calculation of the weighted average of all futures (E_f) corresponding to the k nearest neighbors.

Gaussian processes for forecasting multivariate time series

Gaussian processes

A Gaussian process is fully specified by a mean function $m(.)$ and a covariance function $K(.,.)$. For regression, we can write :

$$y_i = f_i + \epsilon_i \tag{1}$$

where $f_i \sim GP(m(.), K(.,.))$ with $m(.)$ the mean function, $K(.,.)$ the covariate function et $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$.

Multi-task Gaussian processes with common mean

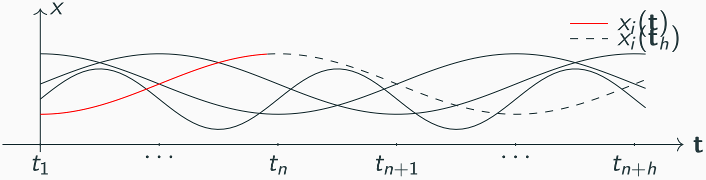


Figure 3: Representation of the multi-task Gaussian process problem

Two different approaches are proposed :

- MAGMA [1] : $y_i = \mu_0 + f_i + \epsilon_i$
- MagmaClust [2] : $y_i = \mu_k + f_i + \epsilon_i$

with $\mu_0 \sim GP(m_0(.), K_{\theta_0}(.,.))$ the mean GP common to all individuals, $\mu_k \sim GP(m_k(.), K_{\theta_k}(.,.))$ the common mean GP of the cluster k, $f_i \sim GP(m(.), K(.,.))$ the specific GP of the i-th individual et ϵ_i the noise.

MagmaKNN

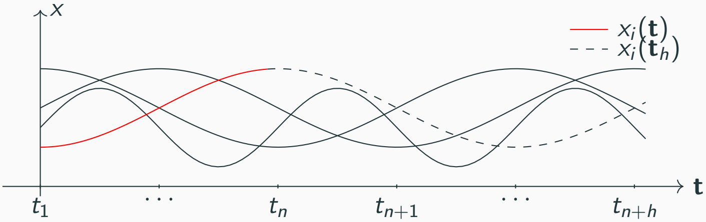


Figure 4: Representation of the multi-task Gaussian process problem

To use multi-task Gaussian processes in our context, we propose a new method MagmaKNN :

- Cutting the curves to obtain a sample of past/future sub-curves (curves in black).
- Selection of the k nearest neighbors of the target curve (curve in red).
- Using MAGMA with the reduced sample size.

Experiments

Experiments design

Data are from the electricity Spanish market (`www.omie.es`) where the objective is to predict electricity prices (expressed in Euro/MWh) and electricity demand (expressed in MW) for the next 24 hours.

- Validation dataset :
  $n = 183$ days, $k = [2, 5, 10, 20]$ and $w = [24, 48, 72, 96]$
- Test dataset : $n = 183$ days with the best hyperparameters.

Validation dataset

Data	Model	w_{best}	k_{best}	RMSE	MAE
Prices	MV-kWNN [4]	24	20	30.14/**25.07**	26.35/21.26
	WNN_{multi}	24	10	**27.63**/25.33	**23.75**/**20.34**
	MagmaKNN	24	10	28.29/24.49	24.06/20.47
Demand	MV-kWNN	24	20	1822.15/1653.6	1605.16/1407.03
	WNN_{multi}	24	20	**1717.87**/**1594.29**	**1504.94**/1359.92
	MagmaKNN	24	20	1835.06/1642.45	1605.39/**1363.5**

Table 1: Means/medians for pattern matching methods

HP for XGBoost : $n_{estimators} = [50, 100, 150]$, max depth $= [5, 10, 15]$ and learning rate $= [0.01, 0.1, 0.3]$.

HP for RF : $n_{estimators} = [50, 100, 150]$ and max depth $= [5, 10, 15]$.

Data	Model	$n_{estimators}$	max depth	learning rate (lr)	RMSE	MAE
Prices	XGBoost	100	10	0.1	**20.97**/**17.1**	**17.28**/**13.67**
	RF	150	15	-	21.78/19.01	18.1/15.27
Demand	XGBoost	50	5	0.1	**1244.01**/**1157.8**	**1024.53**/**956.04**
	RF	150	10	-	1345.86/1166.27	1092.84/966.81

Table 2: Means/medians for machine learning methods

Test dataset

Data	Model	w_{best}	k_{best}	RMSE	MAE
Prices	MV-kWNN	24	20	17.46/**13.62**	14.52/**11.78**
	WNN_{multi}	24	10	**17.2**/14.46	**14.26**/12.25
	MagmaKNN	24	10	19.89/16.17	16.64/13.51
Demand	MV-kWNN	24	20	1359.96/1198.46	1135.08/997.49
	WNN_{multi}	24	20	**1301.85**/**1107.5**	**1081.08**/**909.52**
	MagmaKNN	24	20	1416.59/1147.73	1174/925.82

Table 3: Means/medians for pattern matching methods

Data	Model	$n_{estimators}$	max depth	lr	pdq	RMSE	MAE
Prices	XGBoost	100	10	0.1	-	**15.9**/**12.31**	**12.66**/**10.06**
	RF			-	-	16.33/13.34	13.37/11.24
	ARIMAX	-	-	-	(2,1,2)	26.39/23.23	21.81/19.3
Demand	XGBoost	50	5	0.1	-	**1124.97**/**1001.82**	**931.98**/**808.26**
	RF			-	-	1229.02/1108.13	1021.22/896.32
	ARIMAX	-	-	-	(2,0,1)	5201.45/5222.88	4359.06/4264.51

Table 4: Means/medians for machine learning methods

Conclusion

Conclusion

- With our methods, we provide flexibility to the nearest neighbor search.
- The general idea of nearest neighbor selection is interesting in a multivariate context with many individuals.
- The use of machine learning methods such as XGBoost gives good results and that may be interesting for our general idea of nearest neighbor selection.

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