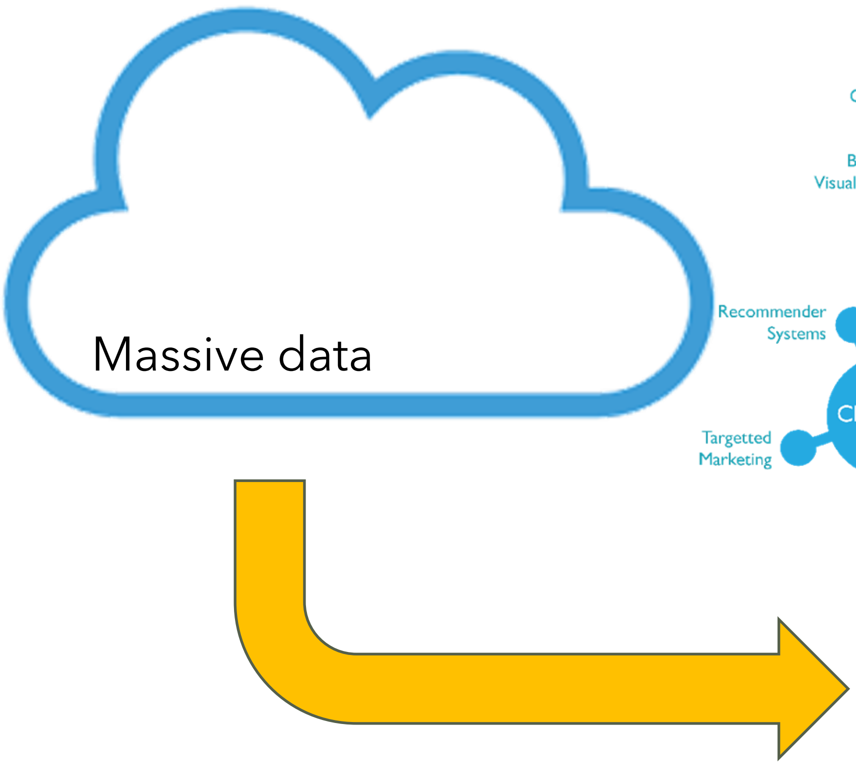
Dynamic Time Scan Forecasting for Renewable Energy Prediction

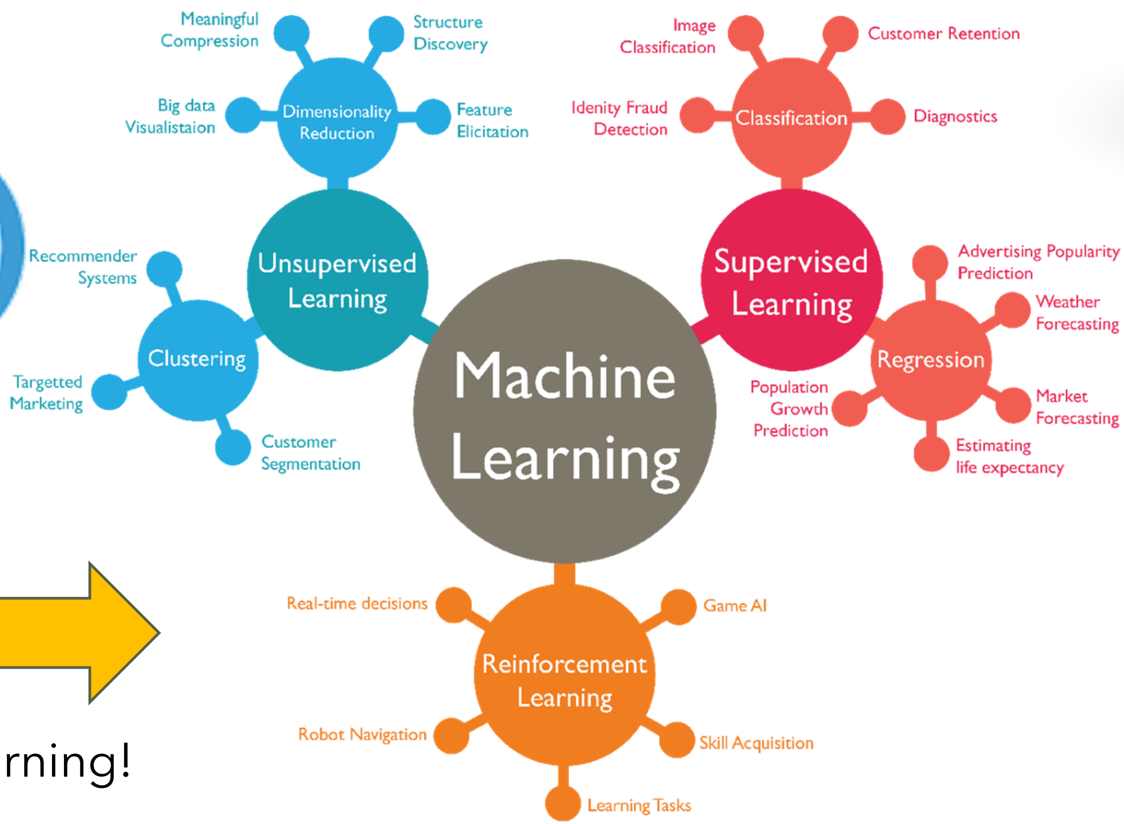
Costa, M. A., **Ruiz-Cárdenas**, R., **Mineti**, L. B., & **Prates**, M. O. (**2021**). Dynamic time scan forecasting for multi-step wind speed prediction. **Renewable Energy**, 177, 584-595.

Just Another Time Series Model ?

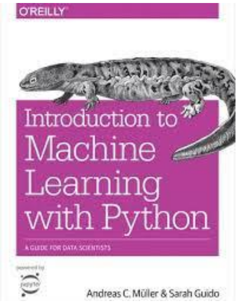
Motivation

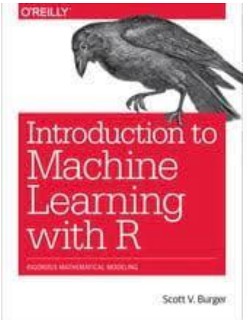


Let´s do Machine Learning!



How many different
Machine Learning methods exist?





Regarding Machine Learning Models:

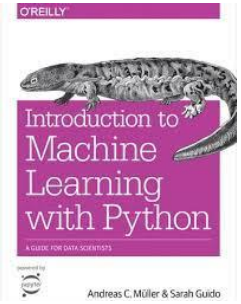
✓ What is your **favorite** Machine Learning model?

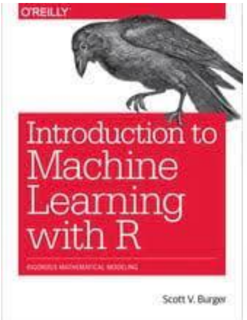
✓ What is your **second** favorite Machine Learning model?

227. xyf (Self-Organizing Maps)

Appendix A: Encyclopedia of Machine Learning Models in **caret**

How many different **Machine Learning** methods exist?





Regarding Machine Learning Models:

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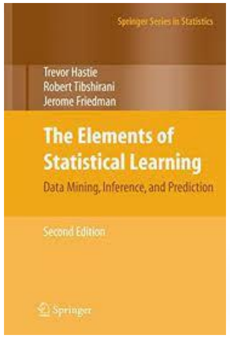
Statistical Elements of **Machine Learning**



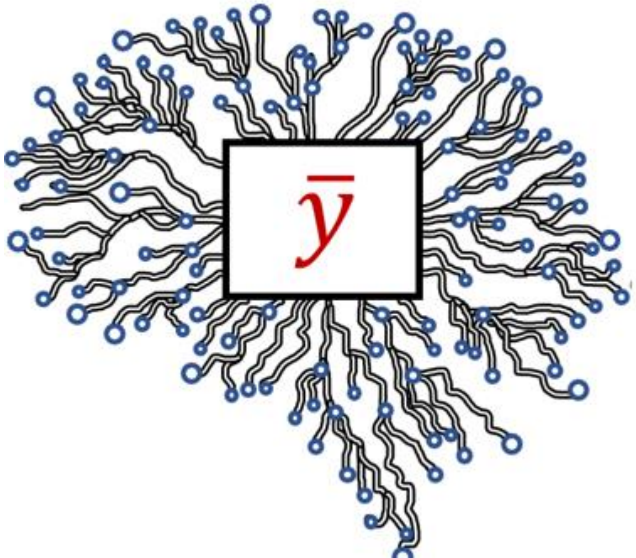
Statistical Decision Theory

$$f(x) = \mathrm{E}(\mathrm{Y}|\mathrm{X} = x)$$

The best prediction of Y at any point X=x is the conditional mean (pg. 18)

Since there is typically at most one observation at any point x, we settle for:

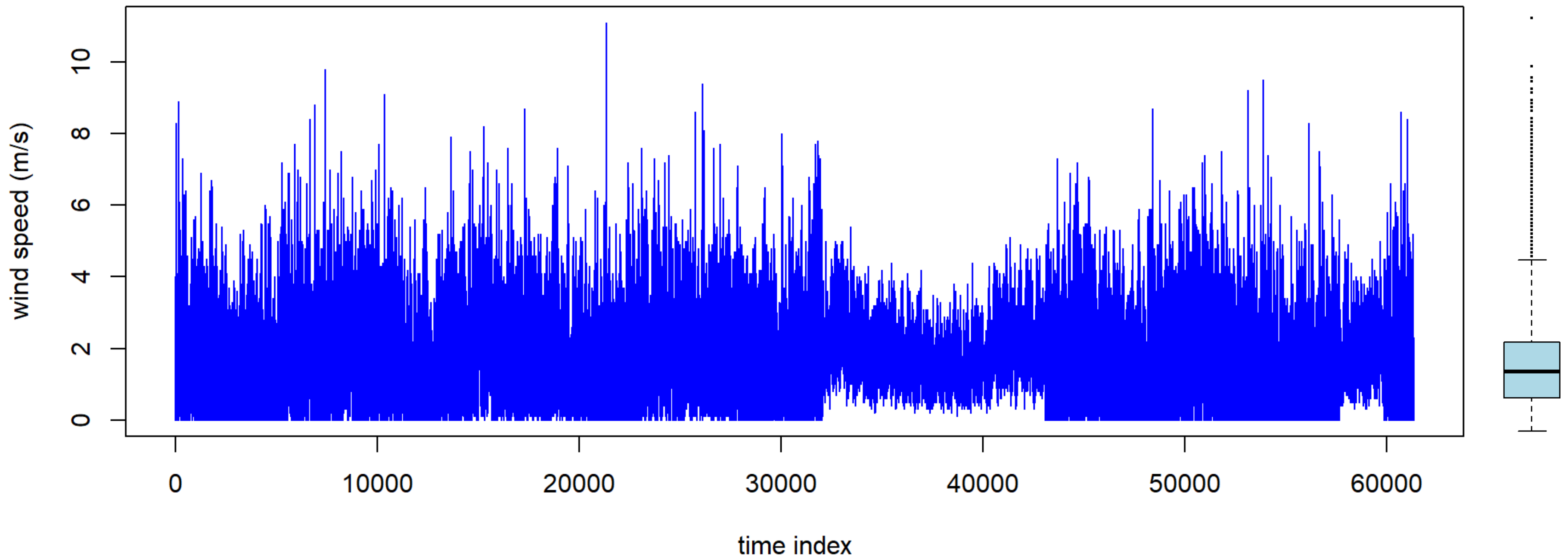
$$\hat{f}(x) = \frac{1}{N_{k(x)}} \sum_{N_{k(x)}} y_i | x$$



The Wind Speed Time Series Case Study

Wind speed data from January 1, 2009 to December 31, 2015 at every 30 minutes (**61.341** observations).

Final goal: one-day-ahead prediction, i.e., 48 Steps ahead



Time Series Forecasting Literature Review

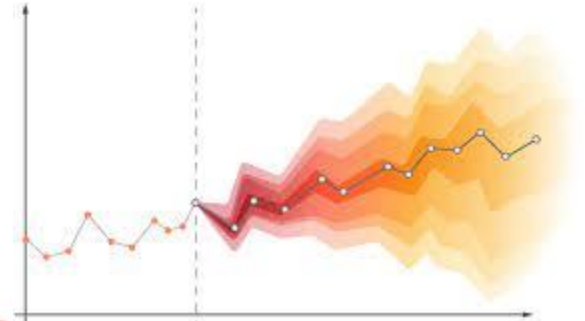
Makridakis Competitions (M-competition)

by Spyros Makridakis

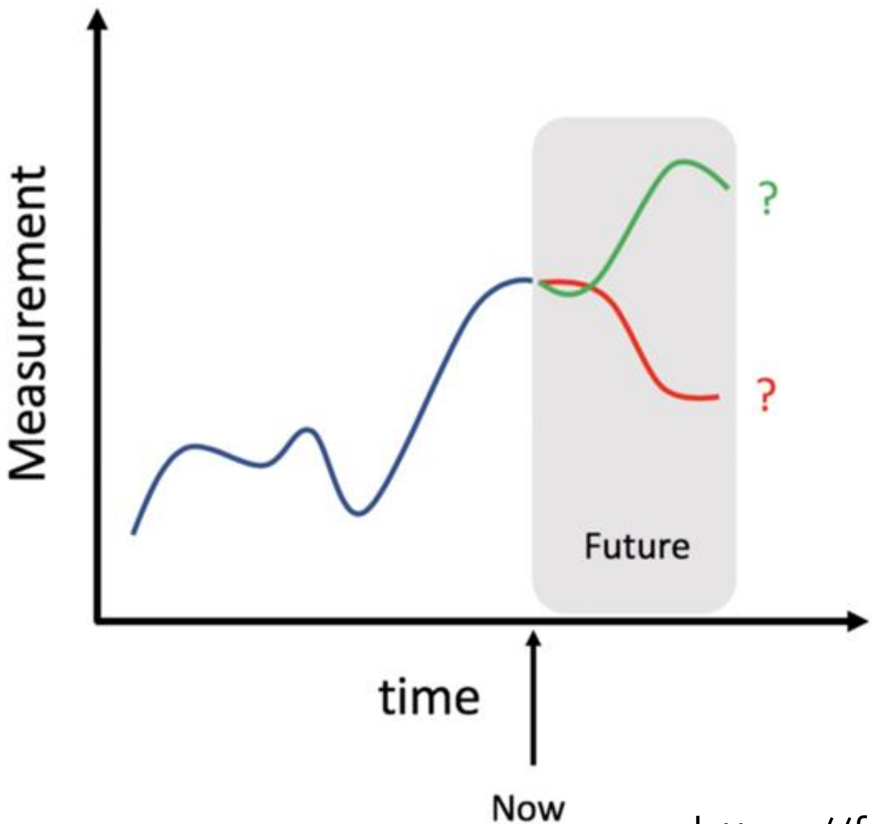
- **M-Competition** (**1982**)
- **M2-Competition** (**1993**)
  - The M2-Competition – A real-time judgmentally based forecasting study (International Journal of Forecasting)
- **M3-Competition** (**2000**)
  - **The M3-Competition: results, conclusions and implications** (International Journal of Forecasting)
- **M4-Competition** (**2020**)
  - The M4 Competition: 100,000 time series and 61 forecasting methods (International Journal of Forecasting)
- **M5-Competition** (**2021**)
  - **M5 accuracy competition: Results, findings, and conclusions** (International Journal of Forecasting)
- **M6-Competition** (**2022-2024**)

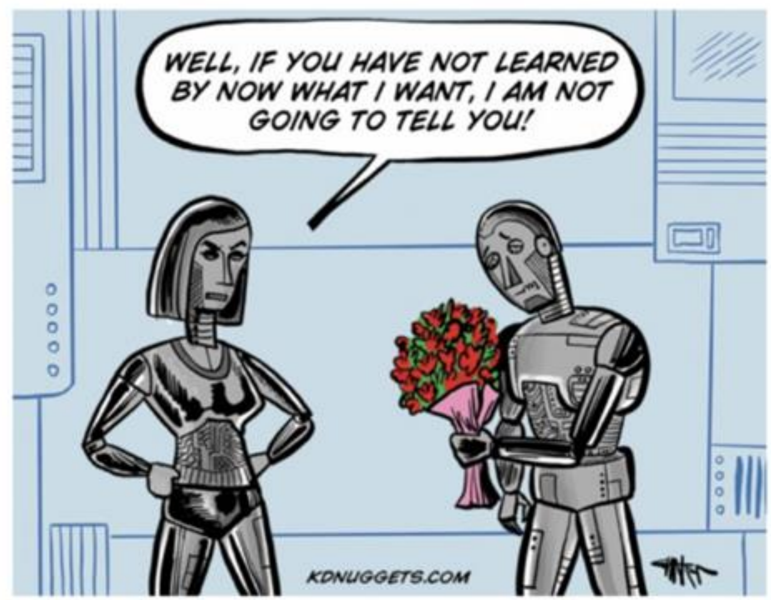
https://forecasters.org/resources/time-series-data/

Main findings



Machine Learning Time Series Problem





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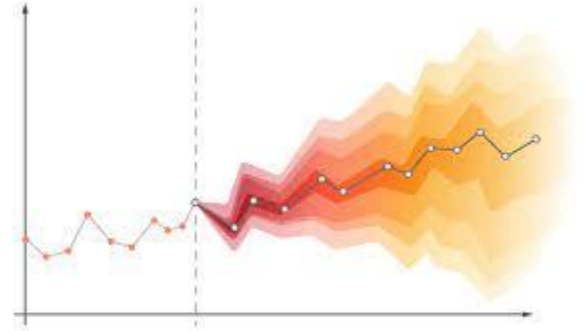
Main findings



- M-Competition (1982)
  - Statistically sophisticated or complex methods do not necessarily provide more accurate forecasts than simpler ones.
- M4-Competition (2020)
  - The combination of methods was the **king** of the M4.
  - The biggest surprise, however, was a "hybrid" approach utilizing both **Statistical and ML features**.
  - **The six pure ML methods submitted in the M4 performed poorly.**

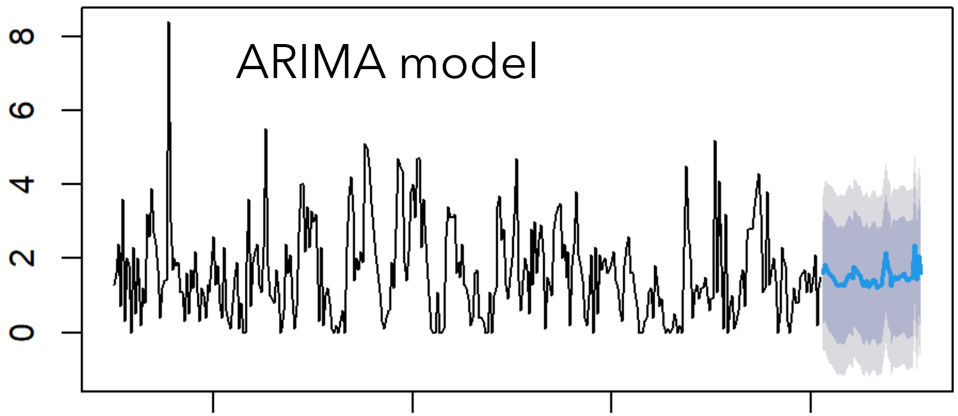
https://forecasters.org/resources/time-series-data/

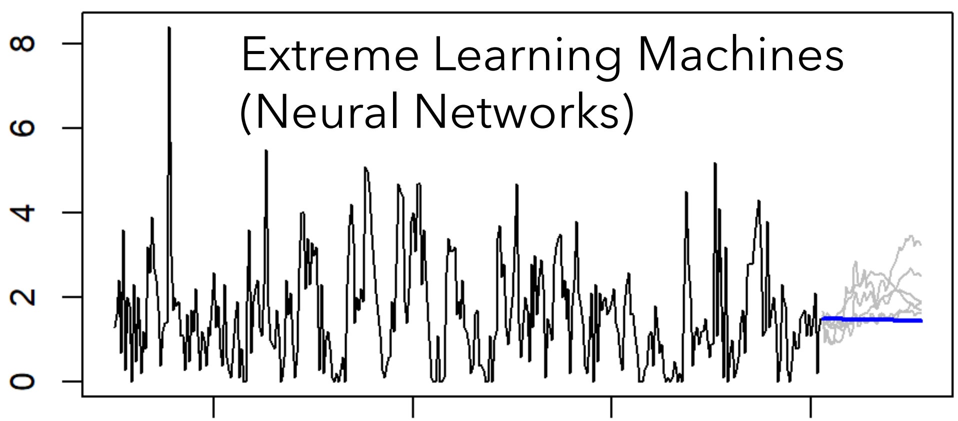
Main findings

- M5-Competition (2021)
  - The M5 "Accuracy" competition clearly showed that **ML methods have entered the mainstream of forecasting applications**, at least in the area of retail sales forecasting.
  - **From a practical perspective, it is necessary to determine the extra costs incurred to run ML methods** versus the standard statistical methods, and whether their accuracy improvements would justify higher costs.

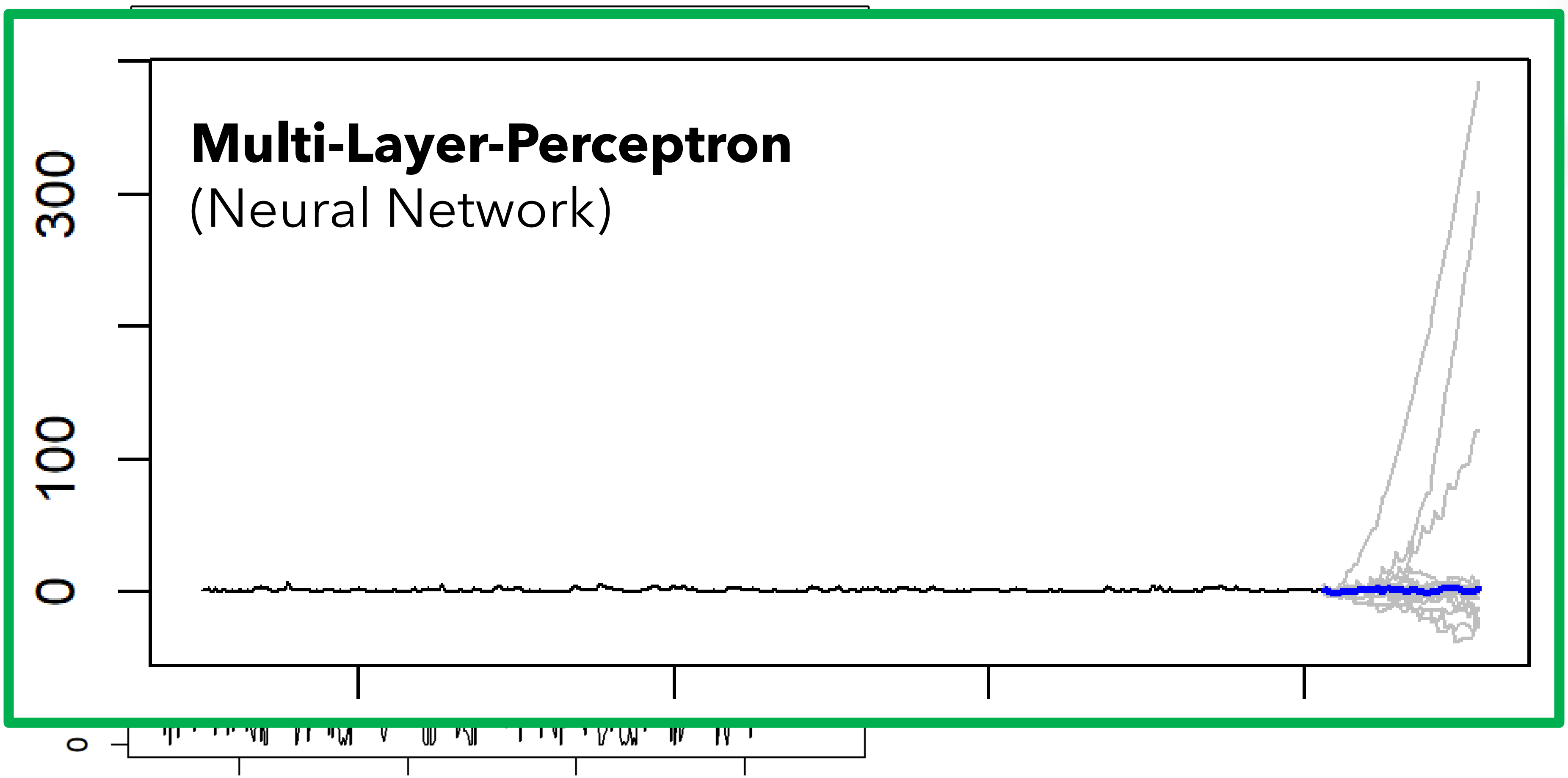
https://forecasters.org/resources/time-series-data/

Some Machine Learning Results for Our Wind Speed Problem





Some Machine Learning Results for Our Wind Speed Problem



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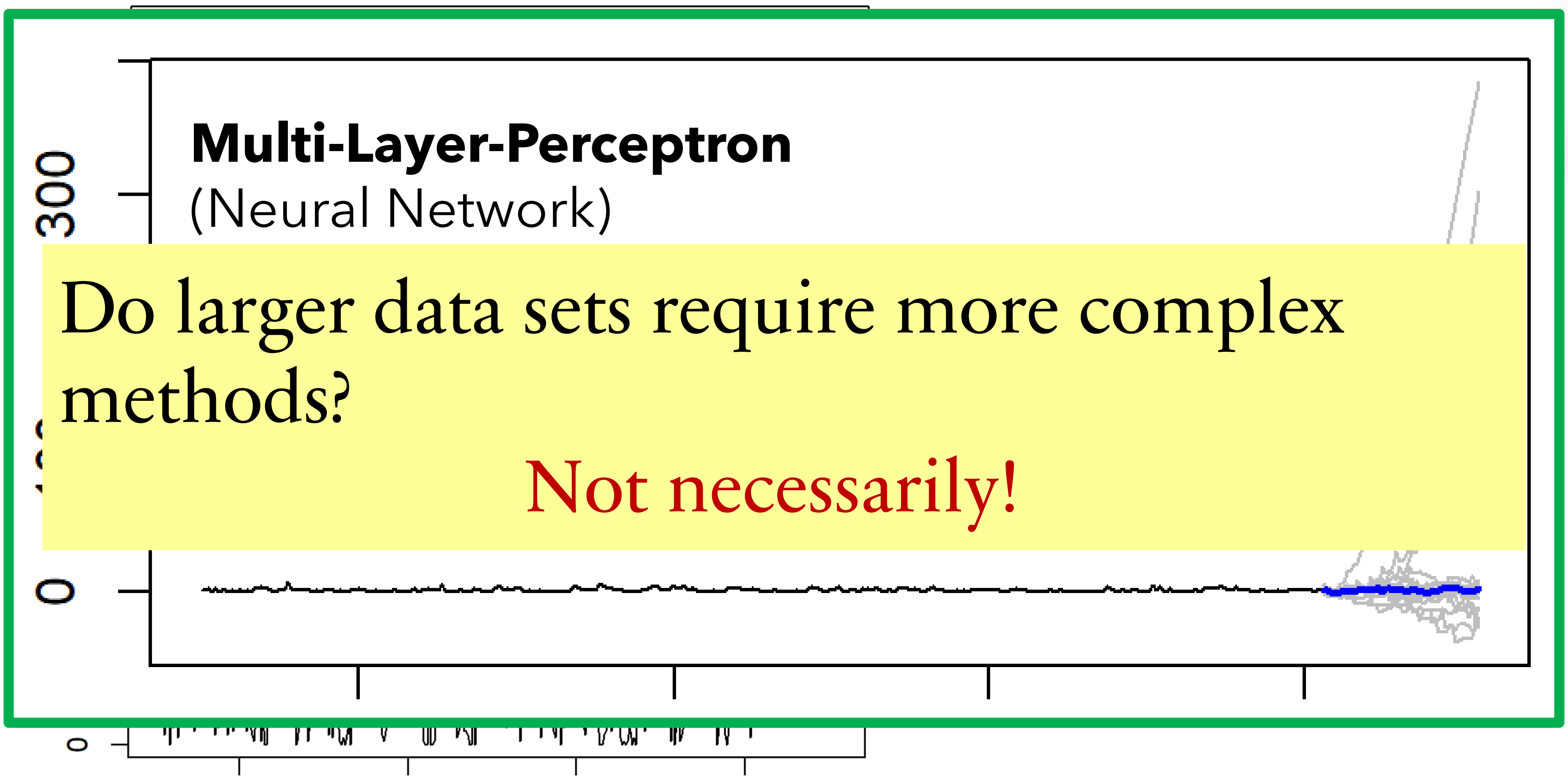


Do larger data sets require more complex methods?

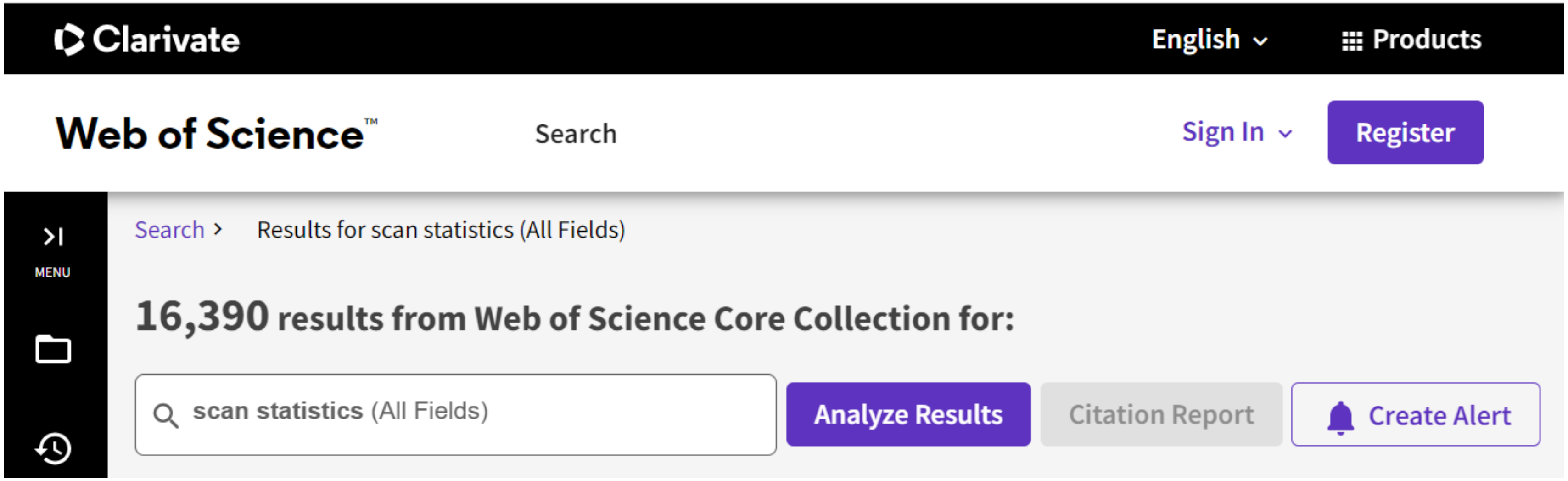
Not necessarily!

Selected methods for Wind Speed (Time Series) Forecasting based on Literature Review

- **Näive method**
  - replicate the observed wind speed in the previous day, i.e., the last 48 observations, as the forecast values.
- **Time series based approaches**
  - TBATS (Exponential smoothing state space model with Box-Cox transformation, ARMA errors, Trend and Seasonal components) model
  - ARIMA (Autoregressive Integrated Moving Average) model
- **Hybrid approaches**
- **Machine learning approaches**
- **Analog-based approches**
  - PSF (Pattern Sequence-Based Forecasting) algorithm
  - AnEn (weather analogs ensemble) method
  - **D**ynamic **T**ime **S**can **F**orecasting (Renewable Energy, 2021)

Scan Statistics

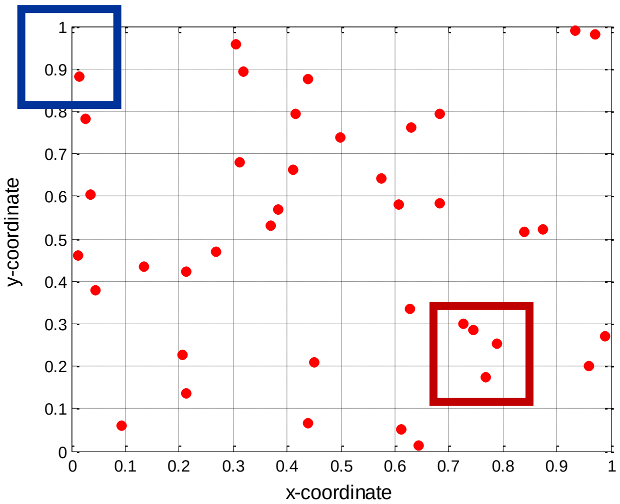
- ✓ Clustering of random points in two dimensions. **Biometrika** 52 (1965), 263-267.
- ✓ Kulldorff M. A spatial scan statistic. **Communications in Statistics: Theory and Methods**, 1997; 26:1481-1496.



November 9, 2022

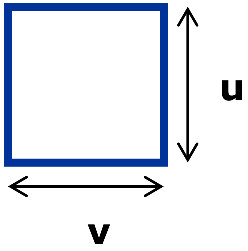
Clustering of random points in two dimensions

by J. I. Naus



Objective: (anomaly detection) to obtain the upper and lower bounds of the probability of finding at least one cluster of dimensions **v** and **u** containing at least **n** points,

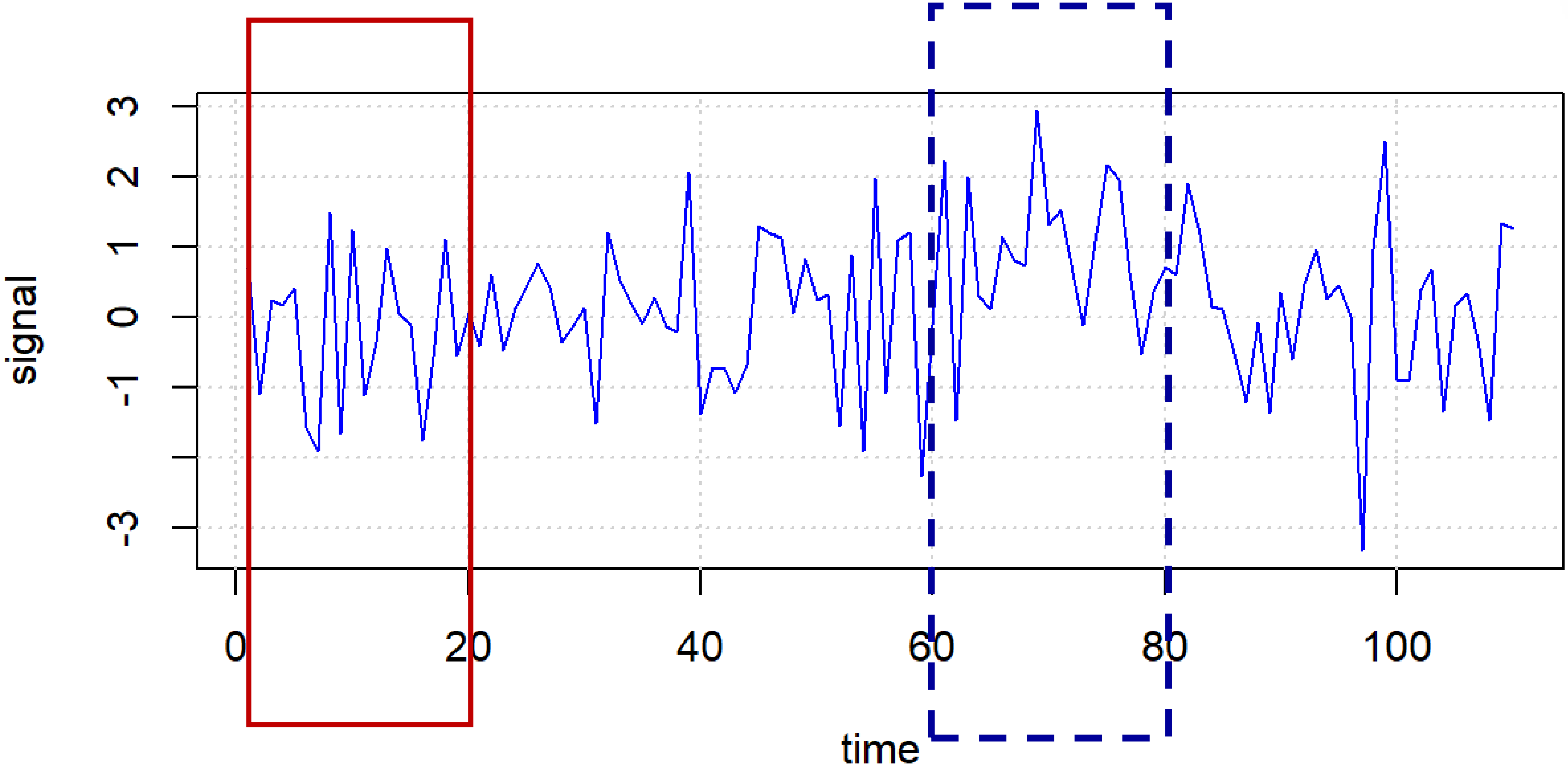
$$P(n \mid N, u, v).$$



Clustering of random points in two dimensions. *Biometrika* **52** (1965), 263-267.

Scan Statistics in Time Series

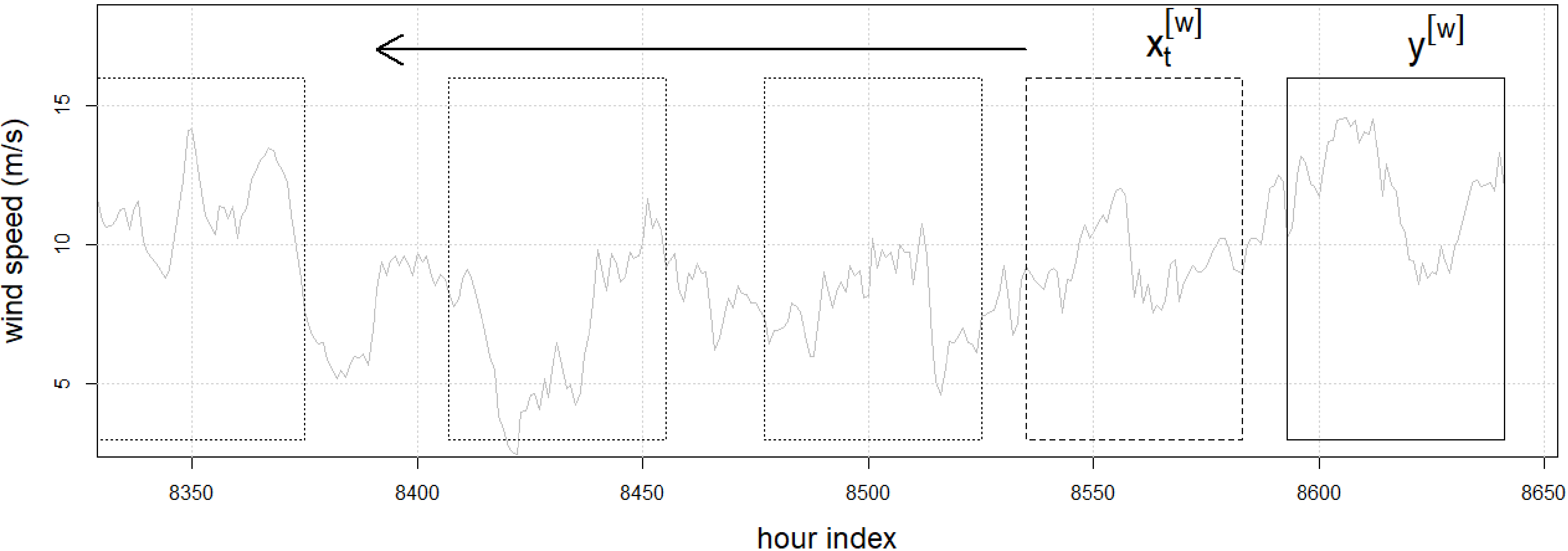
Scanning window



$$\hat{\mu}_{inside} \neq \hat{\mu}_{outside}$$

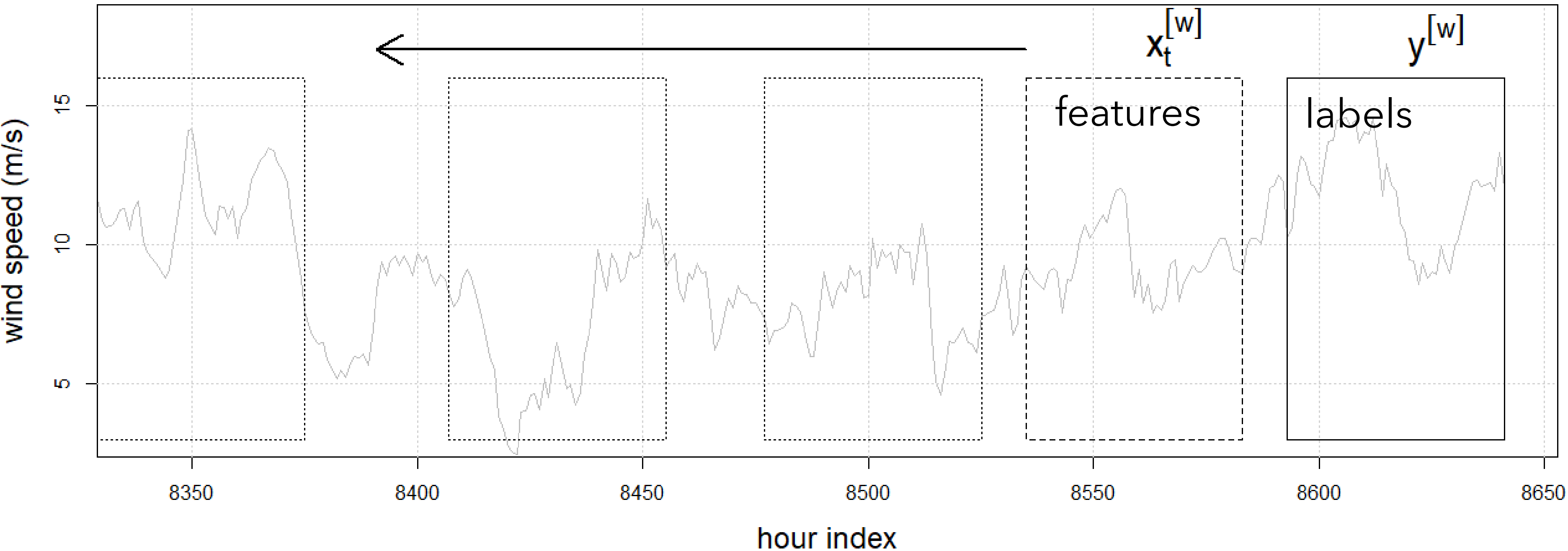
Dynamic Time Scanning Process

Scanning process



Dynamic Time Scanning Process

Scanning process



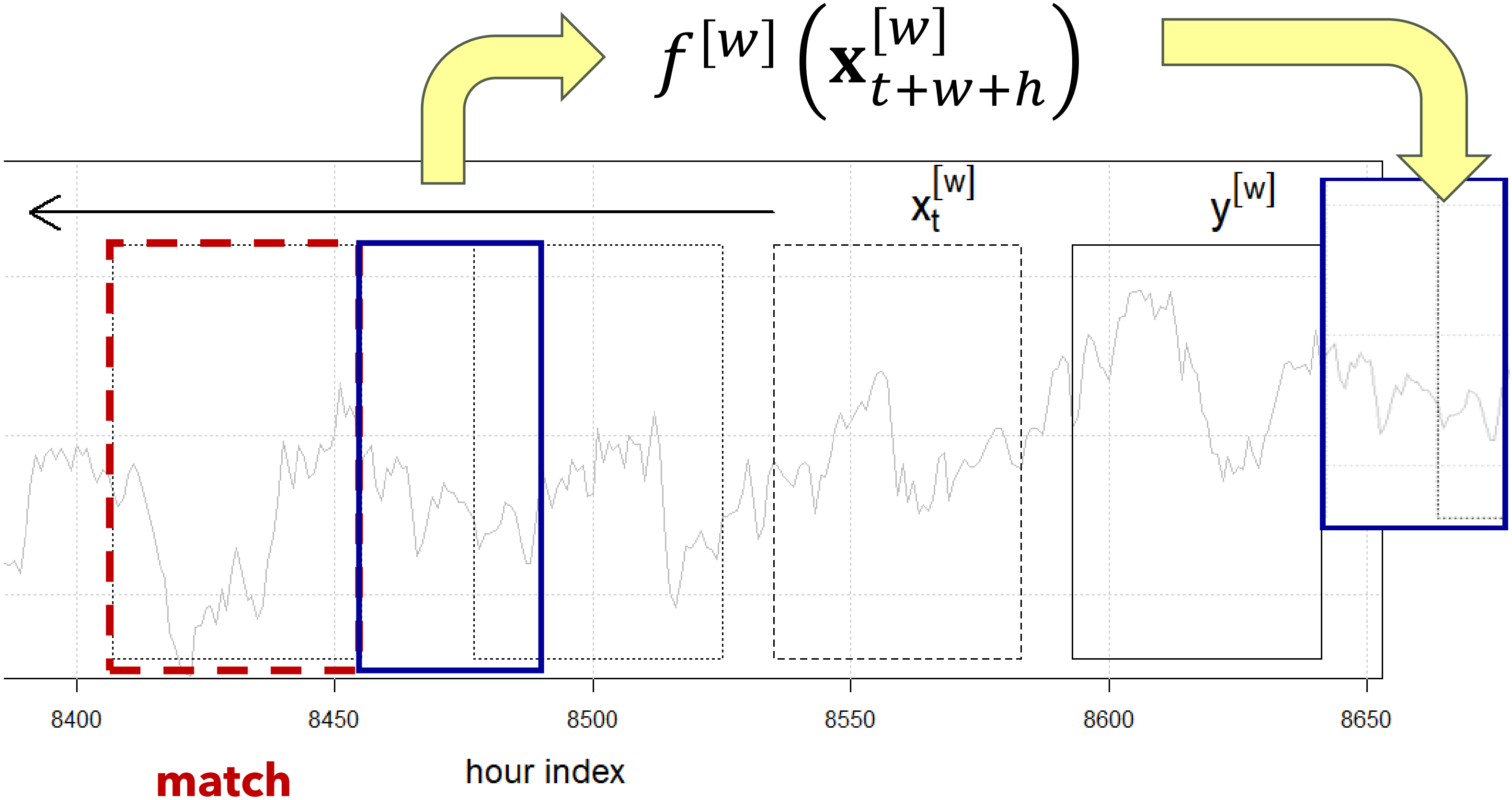
$$y^{[w]} = \beta_0^{[w]} + \beta_1^{[w]} \mathbf{x}_t^{[w]}$$

Similarity function:

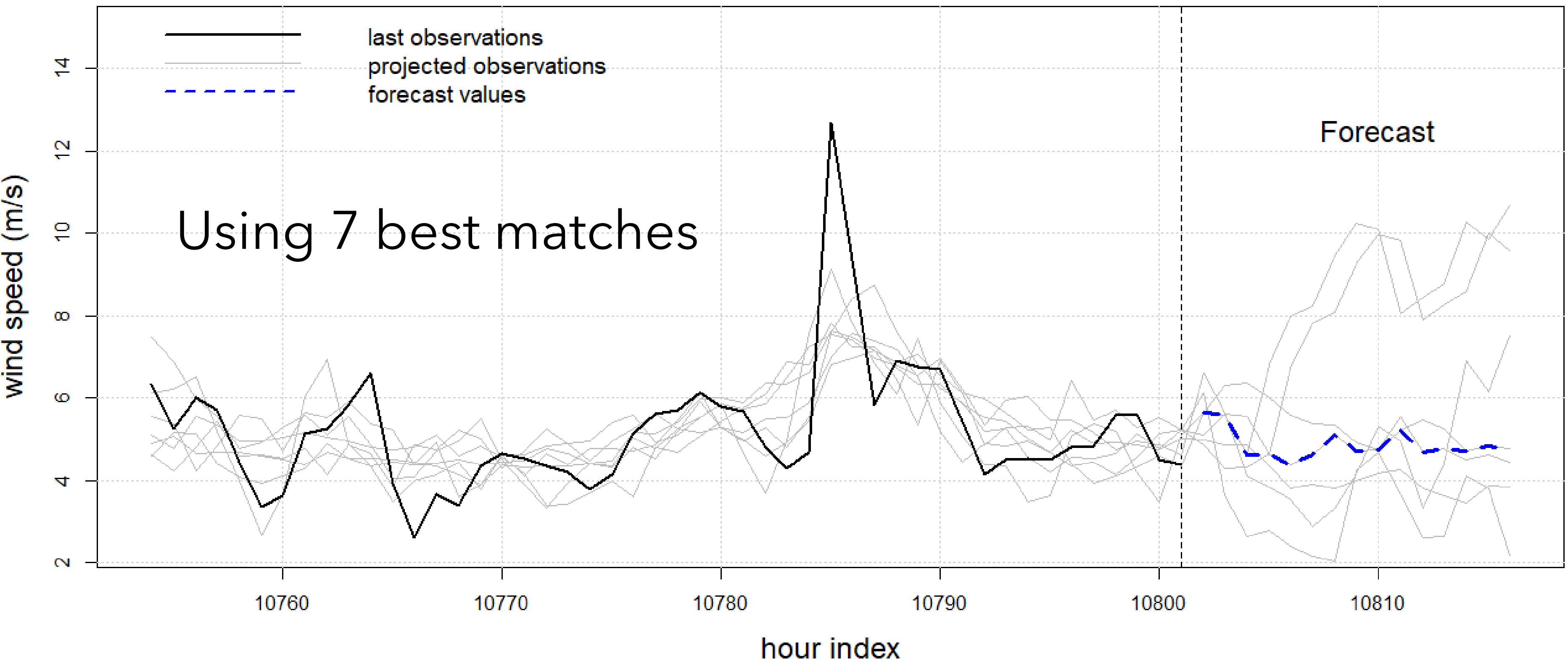
$$y^{[w]} = f\left(\mathbf{x}_t^{[w]}\right)$$

Dynamic Time Scan Forecasting

$$f^{[w]}\left(\mathbf{x}_{t+w+h}^{[w]}\right)$$

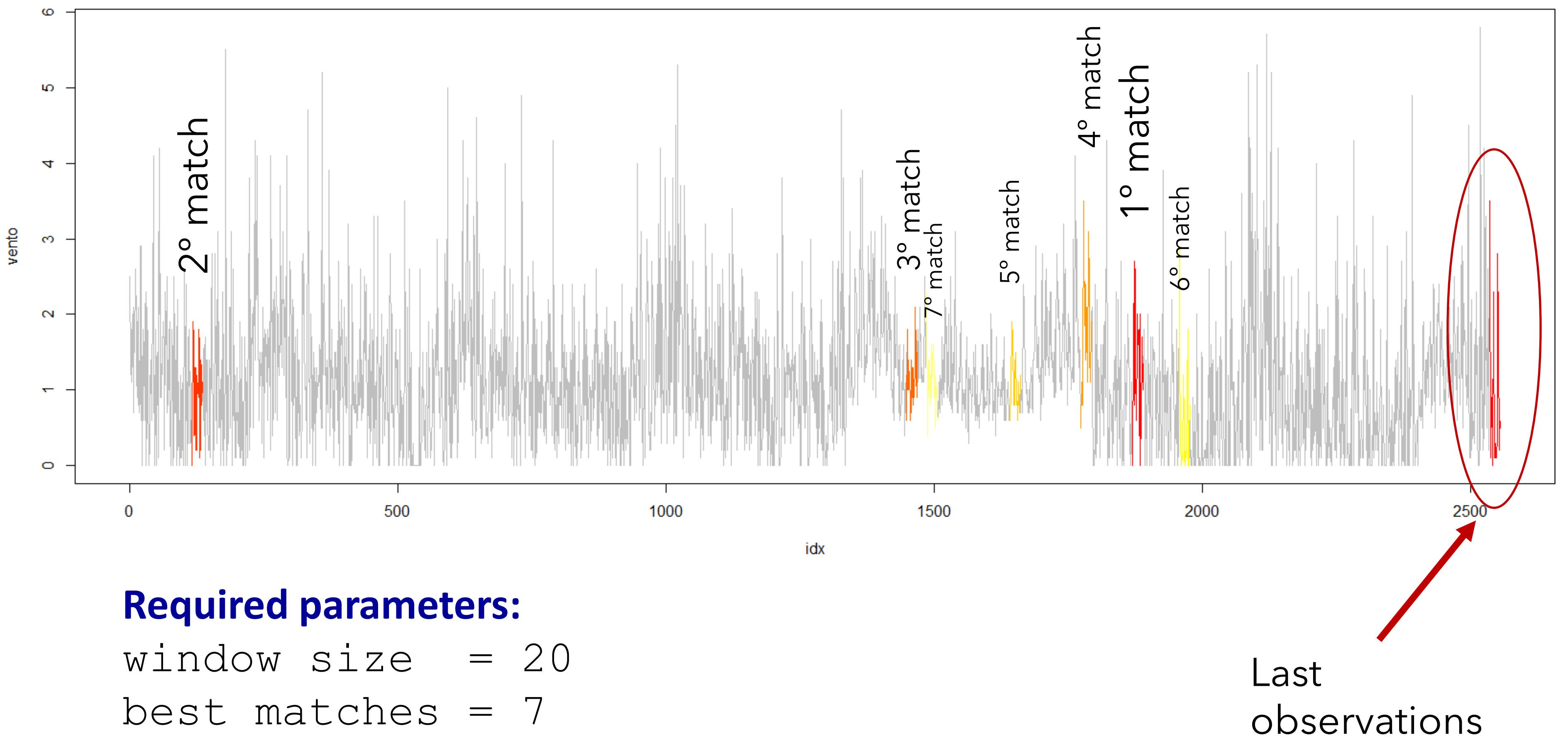


Dynamic Time Scan Forecasting



The **median** function is used to create the final point forecasts to minimize extreme values

Case study



Required parameters:

```
window size  = 20
best matches = 7
k.prediction = 48       (forecast steps)
```

Parameter tuning

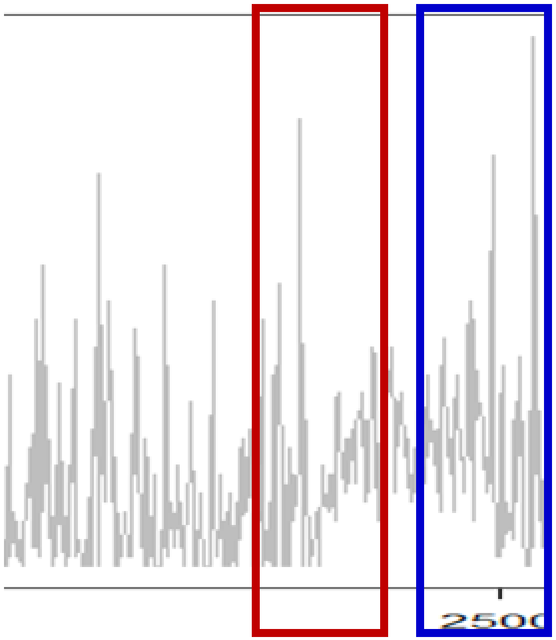
1) **Window size**:
   - 18, 24 e 36 days
2) **f(x): Similarity function:**

$$y = \beta_0 + \beta_1 x \quad \text{(linear)}$$

$$y = \beta_0 + \beta_1 x + \beta_2 x^2$$

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3$$

3) **Best matches**
   - 5, 12, 24

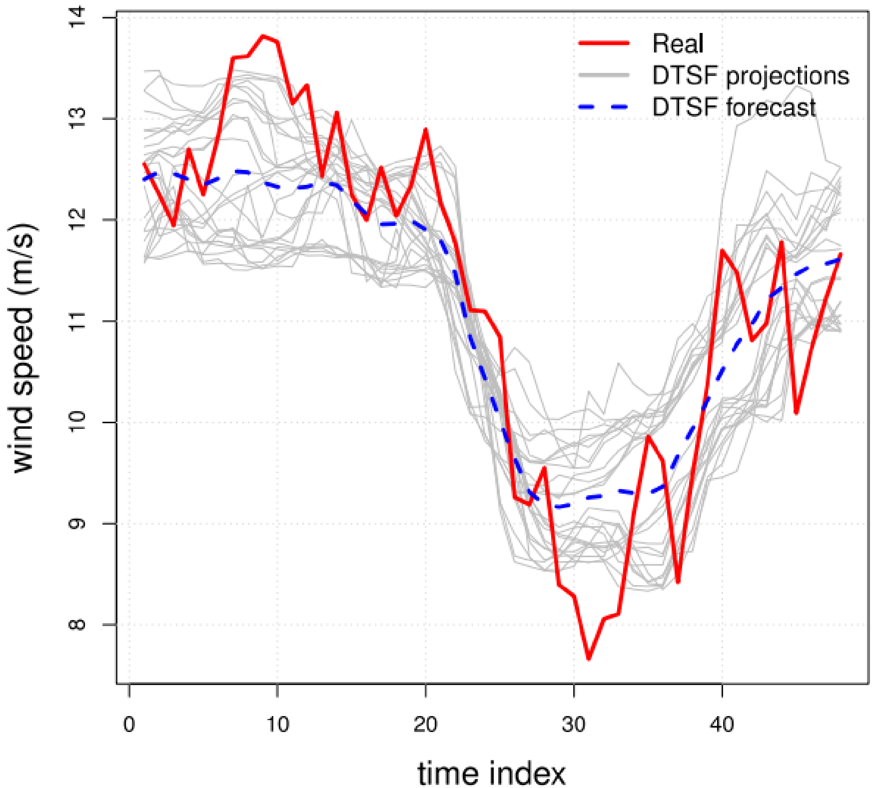


Ensemble version: combining the n elements of a grid of parameters with best forecast performance in the previous day.

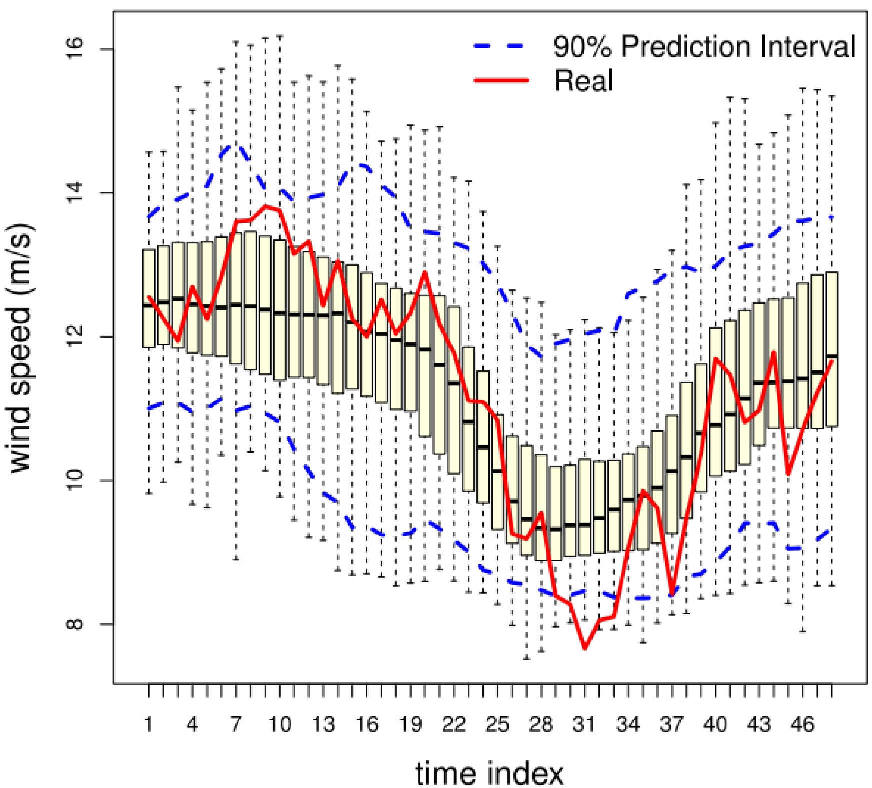
scanning window: 96, 192, 288, 384 and 480
best matches : 5,10, 30, 50, 70 and 90
Similarity functions of degrees: 1, 2 and 3

120 different combinations of the three parameters.

Ensemble Dynamic Time Scan Forecasting



(a) Projected values.



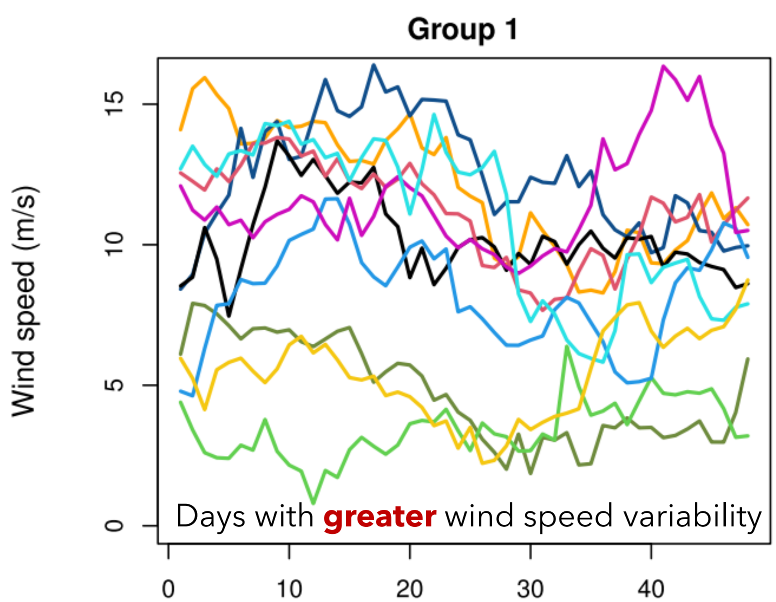
(b) Empirical prediction interval.

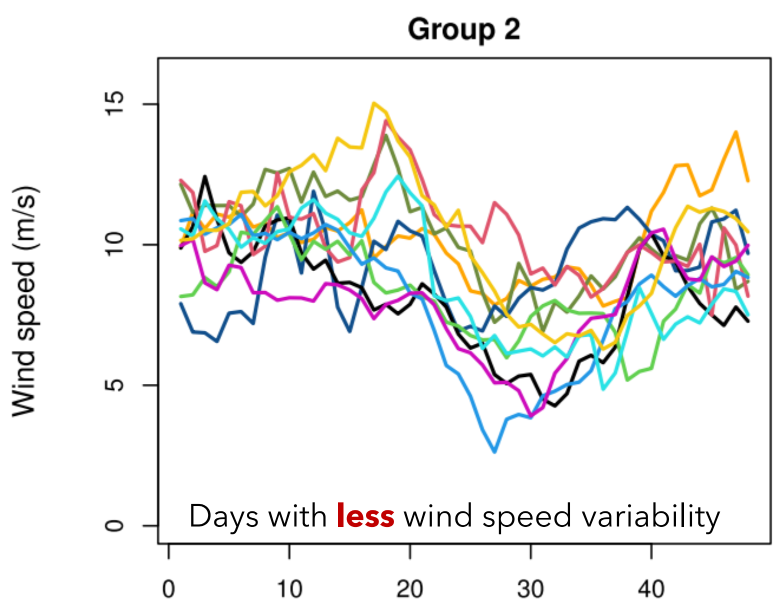
Data Validation

November 21, 2011 to June 22, 2016 (241,200 observations)

Winter	Spring	Summer	Autumn
2015-06-28	2015-09-30	2016-01-31	2016-04-03
2015-07-04	2015-10-01	2016-02-05	2016-04-05
2015-08-08	2015-10-26	2016-02-24	2016-04-12
2015-08-11	2015-12-02	2016-02-25	2016-04-13
2015-09-18	2015-12-06	2016-03-13	2016-05-18

Divided into two groups based on the variability of the wind speed through its diurnal cycle, as influenced by the prevalent turbulence intensity





Forecast objective: 48 steps ahead – next 24 hours.

Error Statistics for Time Series Analysis

(based on the literature review)

$$MAE = \frac{1}{k}\sum_{i=1}^{k}\left|y_{t_i} - \hat{y}_{t_i}\right|,$$

Mean **A**bsolute **E**rror

Root **M**ean **S**quared **E**rror

In general, the lower the better!

$$sMAPE = \frac{2}{k}\sum_{i=1}^{k}\frac{\left|y_{t_i} - \hat{y}_{t_i}\right|}{\left|y_{t_i}\right| + \left|\hat{y}_{t_i}\right|},$$

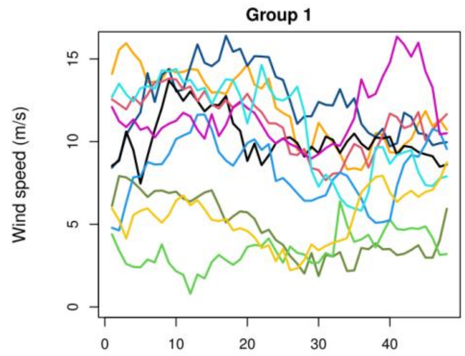
symmetric **M**ean **A**bsolute **P**ercentage **E**rror

$$MF = k \times \frac{\sum_{i=1}^{k}\left(y_{t_i} - \hat{y}_{t_i}\right)^2}{\left(\sum_{i=1}^{k} y_{t_i}\right)^2},$$

Model **F**itting

Results
(using different error statistics)

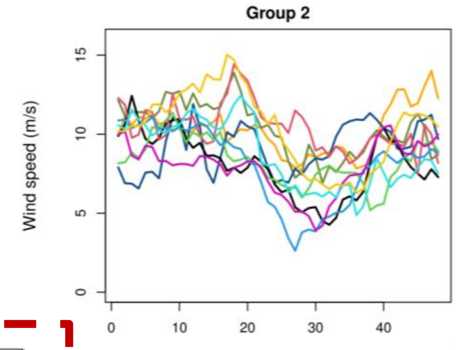
Days with **greater** wind speed variability



Method	MAE	RMSE	sMAPE	MAPE	MF	AvgRelMAE
naïve	2.36	2.79	0.31	31.45	0.0032	1.000
ARIMA	2.27	2.60	0.31	34.00	0.0033	0.989
TBATS	2.04	2.39	0.28	29.47	0.0025	0.935
NNET.1(*)	1.96	2.34	0.27	28.25	0.0028	0.903
NNET.2	2.04	2.39	0.28	26.59	0.0023	0.900
STL+ETS	2.10	2.41	0.29	26.52	0.0022	0.913
hybrid.1	2.16	2.52	0.27	30.32	0.0021	1.007
hybrid.2(*)	1.89	2.22	0.25	25.80	0.0018	0.893
PSF	2.87	3.26	0.38	44.70	0.0047	1.149
AnEn	3.00	3.35	0.38	52.58	0.0096	1.145
forecAn	1.91	2.28	0.27	26.37	0.0021	0.869
DTSF	1.72	2.07	0.23	26.84	0.0021	0.871
eDTSF	1.89	2.27	0.25	26.98	0.0020	0.891

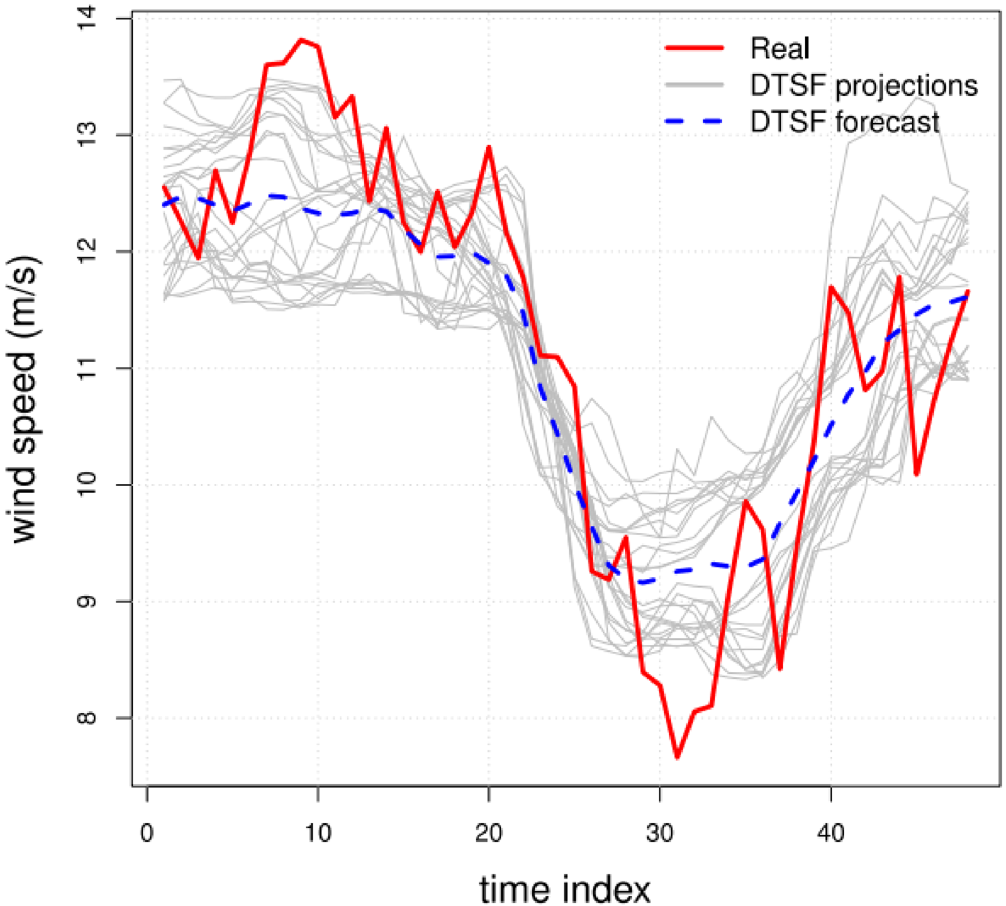
Results

(using different error statistics)



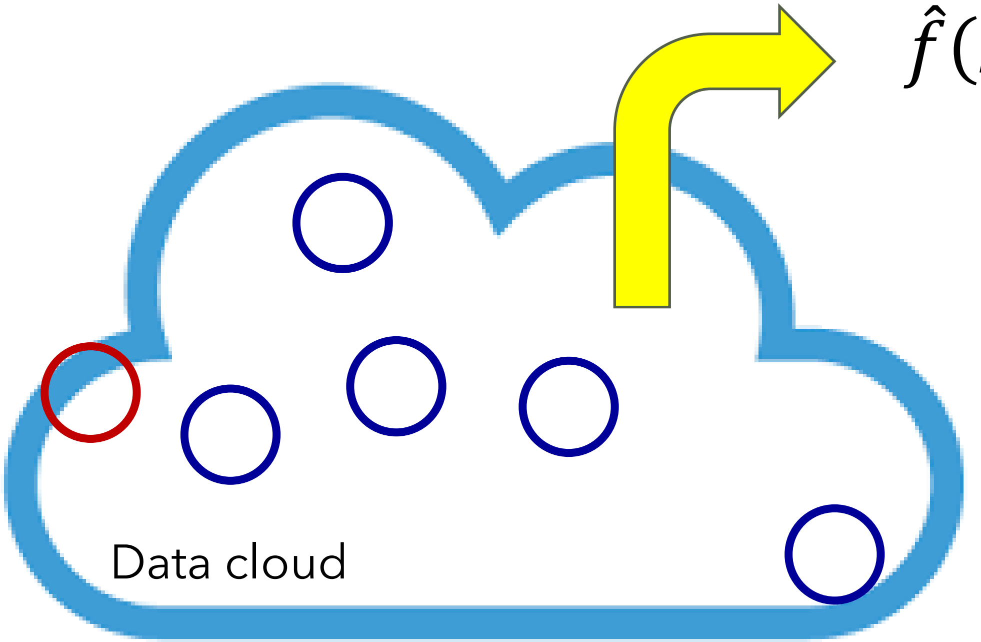
Days with **less** wind speed variability

Method	vgRelMAE
naïve	1.000
ARIMA	0.878
TBATS	0.821
NNET.1(*)	0.909
NNET.2	0.875
STL+ETS	0.890
hybrid.1	1.016
hybrid.2(*)	0.875
PSF	0.928
AnEn	0.908
forecAn	0.866
DTSF	0.931
eDTSF	0.791



(a) Projected values.

Visual conclusion



$$\hat{f}(x) = \frac{1}{N_{k(x)}} \sum_{N_{k(x)}} y_i | x$$

Scanning data may provide a simpler and effective **Machine Learning** solution!

https://github.com/leandromineti/DTScanF

By the way...

M5-competition

"Before presenting the five winning methods, we note that most of the methods utilized **LightGBM**, which is a ML algorithm for performing nonlinear regression using gradient boosted trees (Ke et al., 2017)".

"The **winner** used an equal weighted combination (**arithmetic mean**) of various **LightGBM** models"

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2022). M5 accuracy competition: Results, findings, and conclusions. International Journal of Forecasting.