Bachelor’s Thesis Computer Science Probabilistic Short-term Wind Power Forecasting

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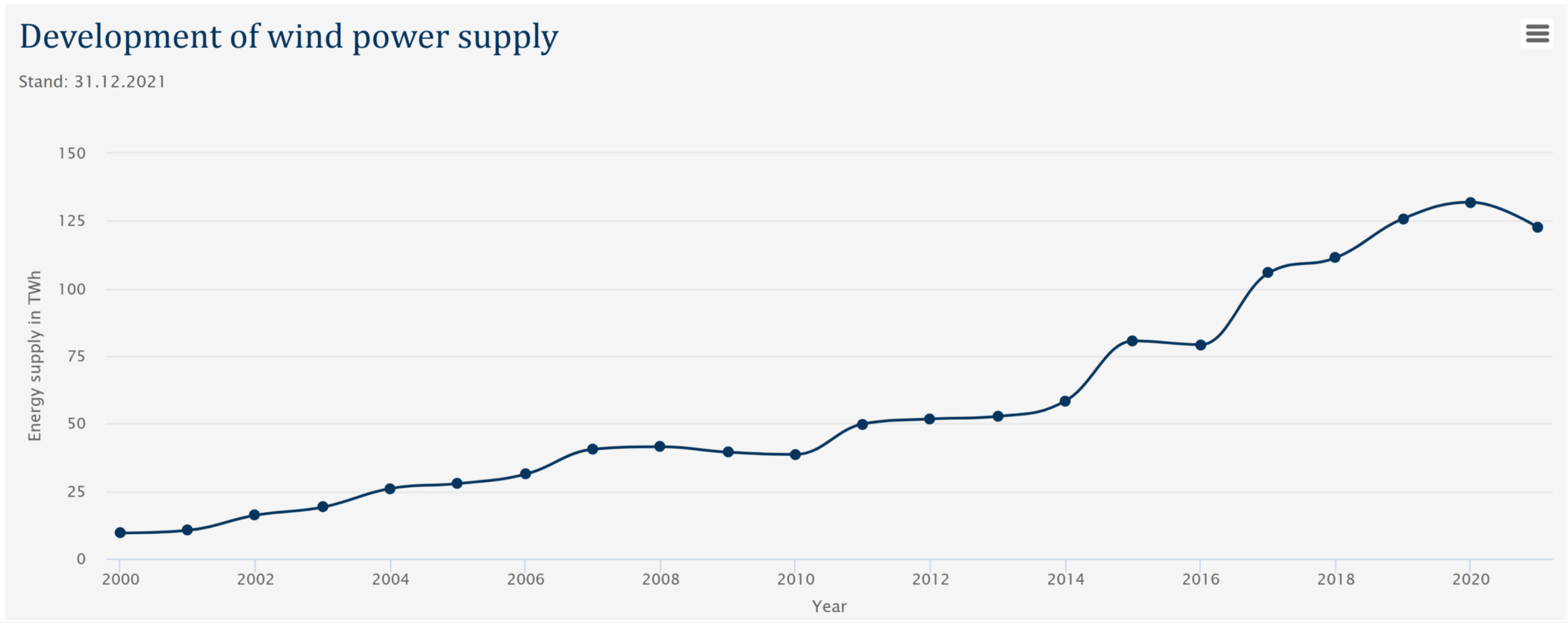
Contents

01 Introduction

Why bother with wind power forecasting?

- to plan and operate a wind power farm
- big shift to renewable energy sources and cope with the shortage of traditional fossil energy and the environmental pollution
- successful integration of large amounts of wind power into the electricity supply system



https://www.wind-energie.de/english/statistics/statistics-germany/

02 Research Question

Research Question

- How to make a wind power forecasting model?
- What is a good approach?
  - Multiple Linear Regression
  - Support Vector Regression
- Which model works better with the dataset?

Approach Breakdown

- Tian, Zhongda (2021). “A state-of-the-art review on wind power deterministic prediction”.
- physical, statistical, and hybrid models
- further divide statistical models into three categories:
  - time series approaches
  - ensemble prediction approaches
  - artificial intelligence approaches
- artificial intelligence model with a supervised machine learning approach
  - Multiple Linear Regression
  - Support Vector Regression

Some literature

- Tawn, R. and J. Browell (2022). “A review of very short-term wind and solar power forecasting”. In: Renewable and Sustainable Energy Reviews 153, doi: 10.1016/j.rser.2021.111758.
- Tian, Zhongda (2021). “A state-of-the-art review on wind power deterministic prediction”. In: Wind Engineering 45.5 doi: 10. 1177/0309524X20941203.
- Wang, Xiaochen, Peng Guo, and Xiaobin Huang (2011). “A Review of Wind Power Forecasting Models”. In: Energy Procedia 12, pp. 770–778. issn: 18766102. doi: 10.1016/j.egypro.2011.10.103.

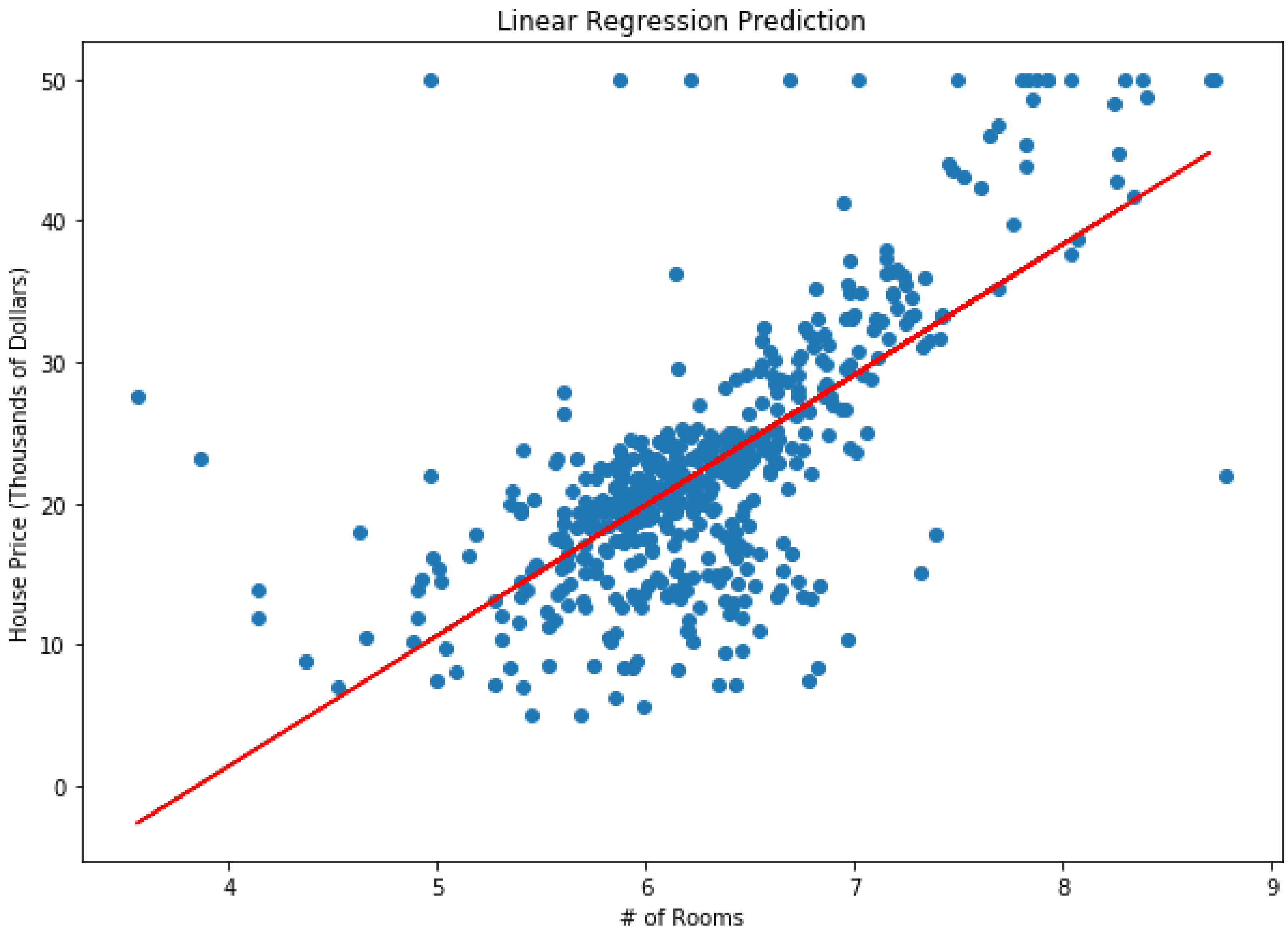
03 Approach

03 Theoretical Approach

- What is Multiple Linear Regression
- What is Support Vector Regression
- What is an Evaluation Score

Multiple Linear Regression

- statistical technique that uses two or more independent variables to predict the outcome of a dependent variable.
- Linear least squares (LLS) is the least-squares approximation of linear functions to data
- Maximum Likelihood estimation



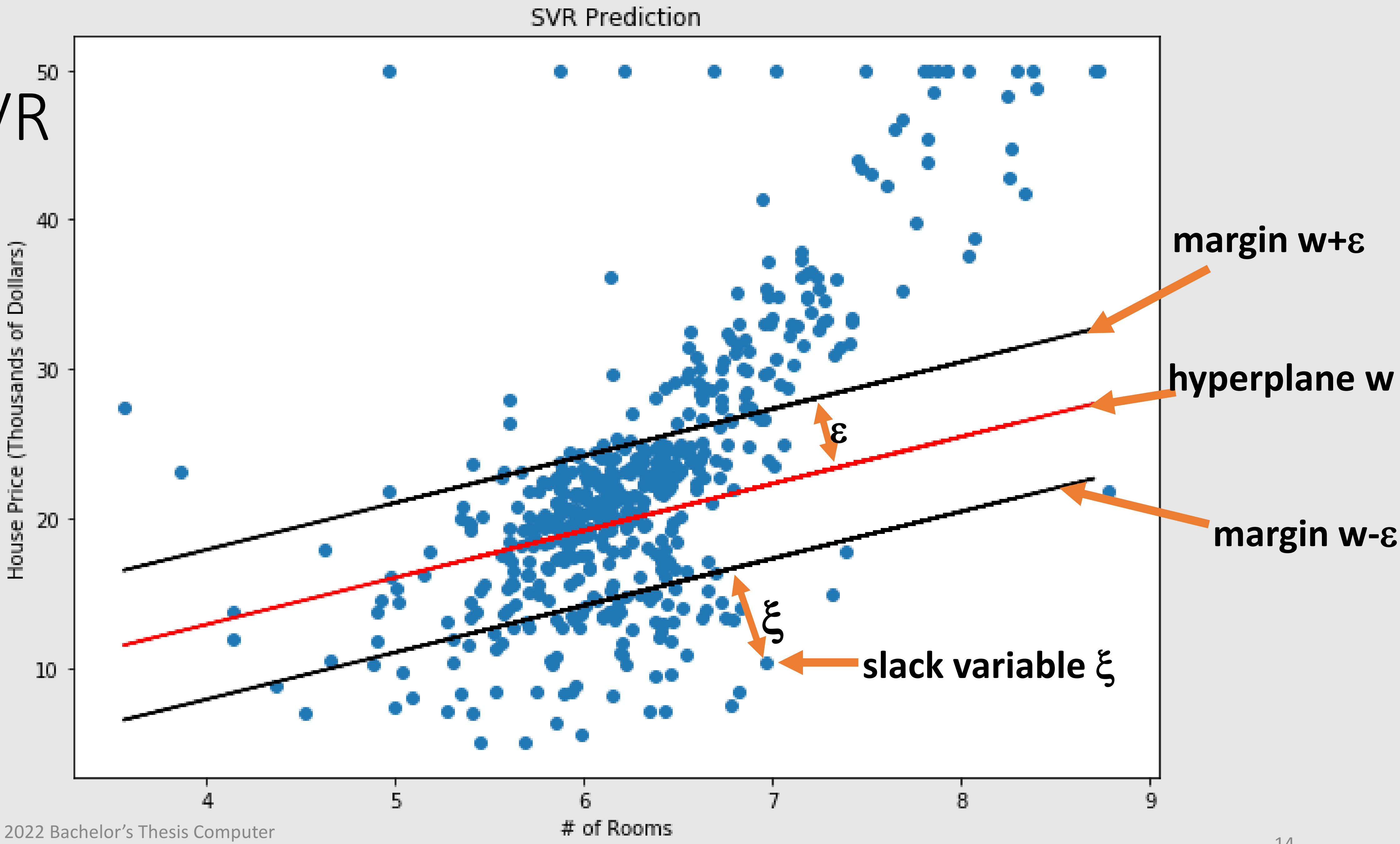
OLS Prediction of Boston Housing Prices

https://towardsdatascience.com/an-introduction-to-support-vector-regression-svr-a3ebc1672c2

Support Vector Regression

- SVM $\Rightarrow$ Classification
- SVR for working with continuous Values instead of Classification
- In simple linear regression, we try to minimize the error rate. In SVR, we try to fit the error within a certain threshold.

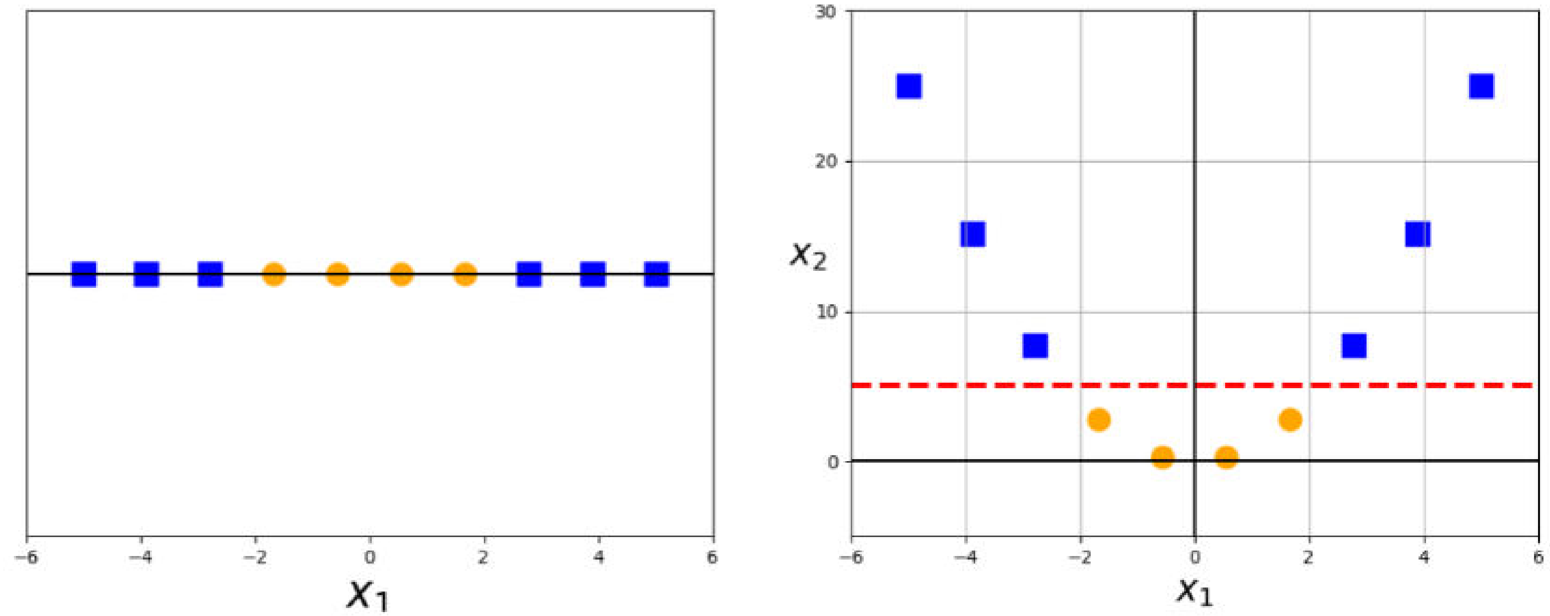
SVR



https://towardsdatascience.com/an-introduction-to-support-vector-regression-svr-a3ebc1672c2

The kernel trick

- Smola, Alex J. and Bernhard Schölkopf (2004). “A tutorial on support vector regression”. In: Statistics and Computing 14.3, doi: 10.1023/B:STCO.0000035301.49549.88



This data becomes linearly separable after a quadratic transformation to 2-dimensions.

https://towardsdatascience.com/the-kernel-trick-c98cdbcaeb3f

Support Vector Regression

- We can choose how tolerant we are of errors, through an acceptable error margin(ϵ) and by tuning our tolerance of falling outside that acceptable error rate
- we can map linear data into a higher feature space to get a better regression curve for the SVR algorithm
    - RBF Kernel
    - Linear Kernel
    - Poly Kernel
    - …

Evaluation Scores

- MAE $\Rightarrow$ mean absolute error
- RMSE $\Rightarrow$ root mean squared error
- R2 $\Rightarrow$ how well the data fit the regression model (the goodness of fit)
- CRPS $\Rightarrow$ comparison of the predicted cumulative density function (CDF) and the true cumulative density function
- Shapley Values $\Rightarrow$ attempt to explain why an ML model reports the outputs that it does on an input

03 Practical Approach

Cleaning the dataset

Feature selection

Multiple Linear Regression model
Support Vector Regression model
parameter and kernel selection

dataset

- La haute borne windfarm in France
- about 150 km to the left of Strasbourg
- 4 turbines
- Data from 2016-12-31 until 2018-01-12
- https://opendata-renewables.engie.com/explore/dataset/01c55756-5cd6-4f60-9f63-2d771bb25a1a/information

https://www.thewindpower.net/windfarm_en_3354_la-haute-borne.php

Feature Selection

- Algorithm
  - recursive feature elimination algorithm
  - select k-Best algorithm
  - tried some features by hand
- evaluate the different features using
  - Multiple Linear Regression model
  - MAE score, RMSE score, CRPS, and R2 score a

Feature Selection

	model 1	model 2	model 3	model 4	model 5	model 6	model 7	model 8	model 9	model 10	model 11	model 12
Ba_avg							x					
Cosphi_avg					x							
Db2t_avg						x						
Gb1t_avg		x	x	x								
Gost_avg	x											
hard coded time stamp												x
month											x	
Nf_avg						x						
Ot_avg	x					x	x	x	x	x	x	x
Rbt_avg	x											
Rs_avg	x											
Rt_avg						x	x		x			
Va_avg						x						
Ws_avg	x				x		x	x				
Ws1_avg			x	x	x				x	x	x	x
Ws2_avg			x	x	x				x	x	x	x
year											x	
Yt_avg		x	x				x		x			
MAE	148.22	218.64	146.02	161.90	156.52	334.84	134.84	160.02	142.99	157.67	157.38	157.11
RMSE	200.16	288.30	192.54	209.55	202.67	453.81	190.18	204.02	191.99	202.56	202.34	202.30
R2	0.80	0.60	0.82	0.79	0.80	0.07	0.83	0.80	0.82	0.80	0.80	0.80
CRPS	142.84	132.55	261.38	275.20	270.80	108.21	238.69	135.35	256.58	273.19	272.57	272.42

Table 3.1: Evaluation scores of different Multiple Linear Regression models using different features to choose the best set of features

Feature Selection

	model 1	model 2	model 3	model 4	model 5	model 6	model 7	model 8	model 9	model 10	model 11	model 12
Ba_avg							x					
Cosphi_avg					x							
Db2t_avg						x						
Gb1t_avg		x	x	x								
Gost_avg	x											
hard coded time stamp												x
month											x	
Nf_avg						x						
Ot_avg	x					x	x	x	x	x	x	x
Rbt_avg	x											
Rs_avg	x											
Rt_avg						x	x		x			
Va_avg						x						
Ws_avg	x				x		x	x				
Ws1_avg			x	x	x				x	x	x	x
Ws2_avg			x	x	x				x	x	x	x
year											x	
Yt_avg		x	x				x		x			
MAE	148.22	218.64	146.02	161.90	156.52	334.84	134.84	160.02	142.99	157.67	157.38	157.11
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Table 3.1: Evaluation scores of different Multiple Linear Regression models using different features to choose the best set of features

- the pitch angle (BA)
- the hub temperature (Rt)
- the nacelle temperature (Yt)
- the wind speed (Ws)
- the outdoor temperature (Ot)

Parameter and Kernel Selection

kernel	C	epsilon	MAE	RMSE	R2	CRPS
rbf	1.0	0.1	77.70	125.46	0.92	127.60
rbf	10.0	1.0	49.73	81.99	0.96	124.08
rbf	100.0	20.0	41.18	64.01	0.98	122.62
rbf	150.0	25.0	40.34	62.02	0.98	122.44
rbf	160.0	40.0	41.55	62.51	0.98	123.01
rbf	170.0	30.0	40.51	61.67	0.98	122.69
rbf	175.0	25.0	39.90	61.32	0.98	122.29
rbf	175.0	30.0	40.44	61.55	0.98	122.55
rbf	180.0	35.0	40.85	61.70	0.98	122.83
rbf	185.0	40.0	41.11	61.85	0.98	122.97
rbf	25.0	5.0	45.92	74.60	0.97	123.41
rbf	250.0	50.0	41.32	61.33	0.98	123.26
rbf	350.0	100.0	48.43	65.70	0.98	131.38
rbf	50.0	5.0	42.75	68.80	0.97	122.83

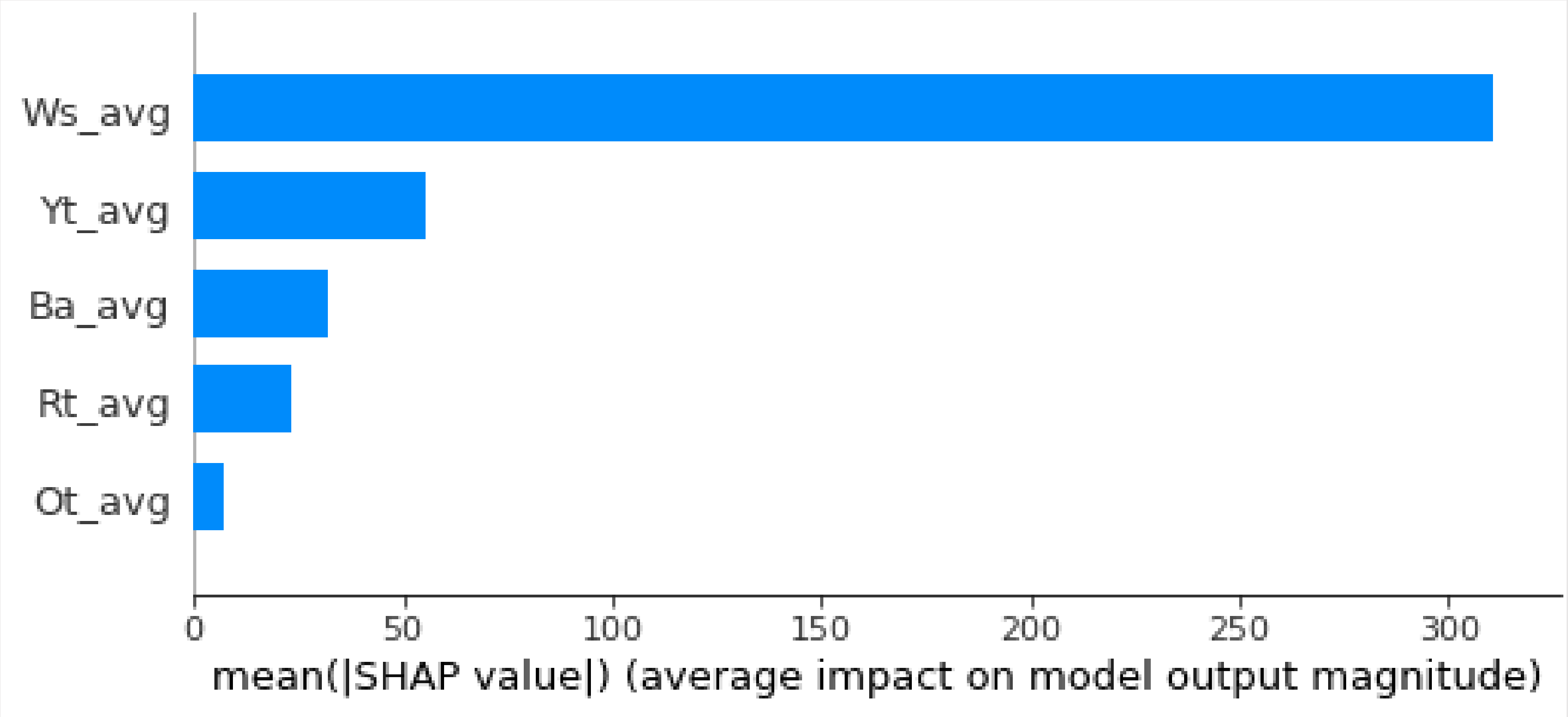
Table 3.3: Evaluation of different parameters to compare different SVR models

kernel	C	epsilon	MAE	RMSE	R2	CRPS
linear	1.0	0.1	116.00	210.76	0.78	151.95
rbf	1.0	0.1	77.70	125.48	0.92	127.60
polynomial	1.0	0.1	132.67	248.66	0.70	117.77

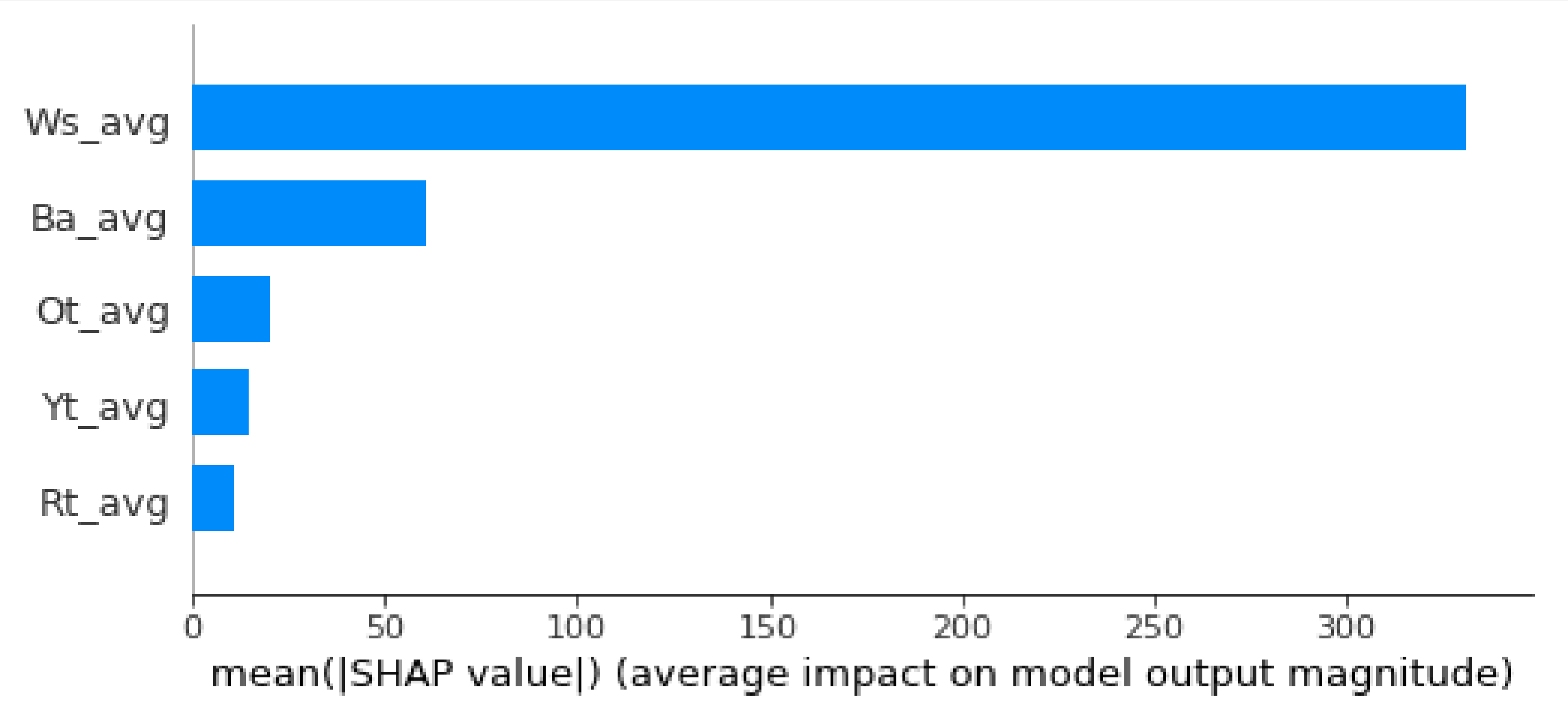
Table 3.2: Evaluation scores for different SVR kernels (linear, rbf, poly)

04 RESULTS

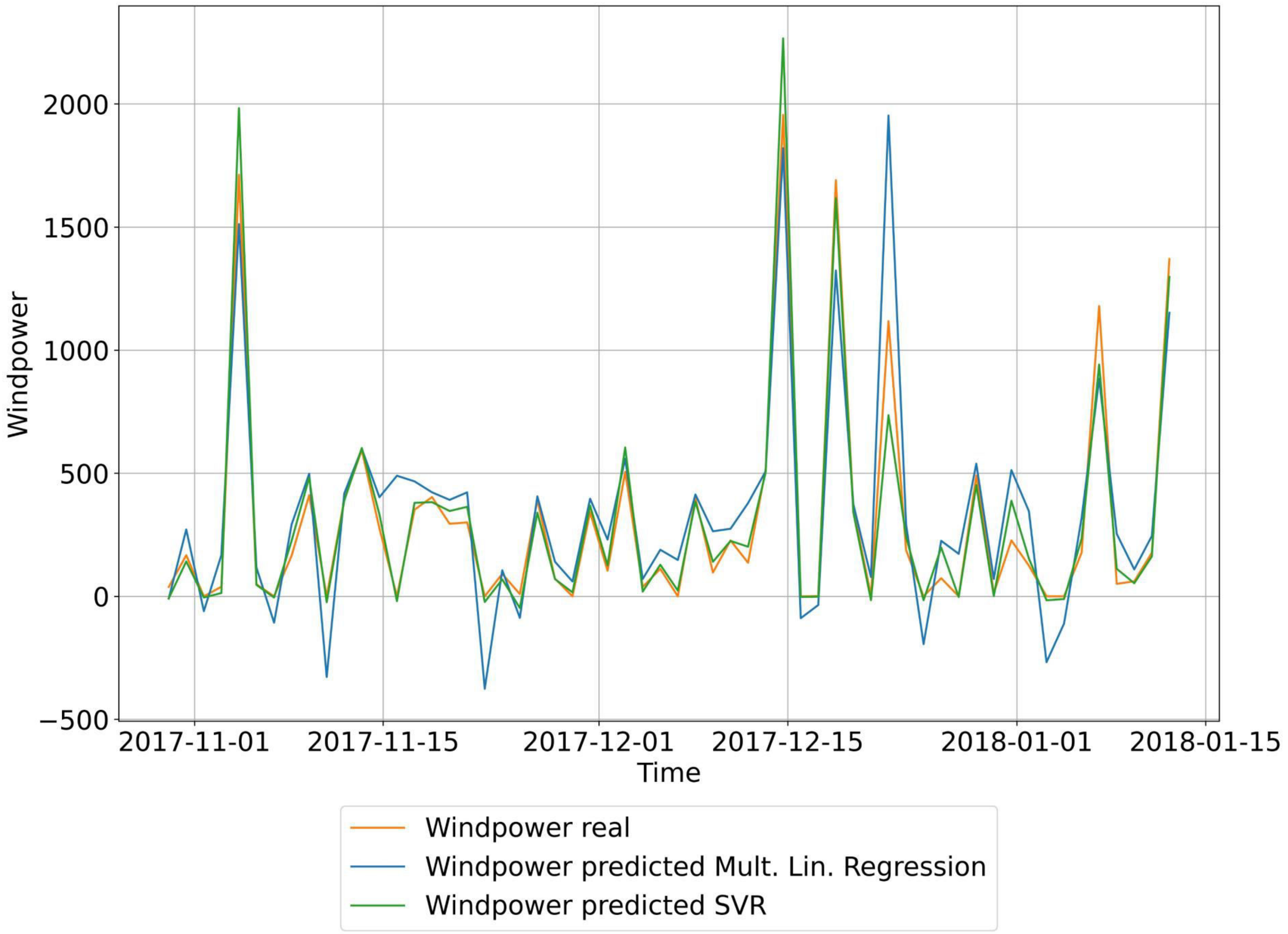
Multiple Linear Regression model



Support Vector Regression model



Comparison



Windpower
2000
1500
1000
500
0
−500
2017-11-01
2017-11-15
2017-12-01
2017-12-15
2018-01-01
2018-01-15
Time
Windpower real
Windpower predicted Mult. Lin. Regression
Windpower predicted SVR

Comparison

	Multiple Linear Regression	Support Vector Regression
MAE	133.29	39.58
RMSE	188.86	60.87
R2	0.829	0.982
CRPS	174.04	122.19

Table 4.1: Evaluation scores to compare the Multiple Linear Regression model to the Support Vector Regression model

05 Conclusion

- Conclusion

- Discussion

Conclusion

- Main work
  - data processing
  - parameter selection
  - modeling a Multiple Linear Regression model
  - modeling a Support Vector Regression model
  - evaluating and comparing the different models

Conclusion

- SVR approach works better for this particular wind farm dataset
- I assume an SVR approach generally works better for wind power prediction than a Multiple Linear Regression approach

Discussion

- Thank you so much for your interest and attention
- Any questions?