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Wind power generation forecasting using explainable artificial intelligence in Jeju Island, South Korea

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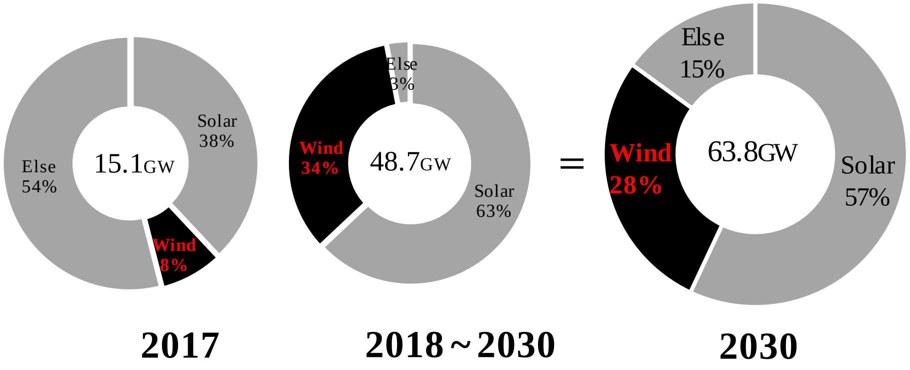
CONTENTS

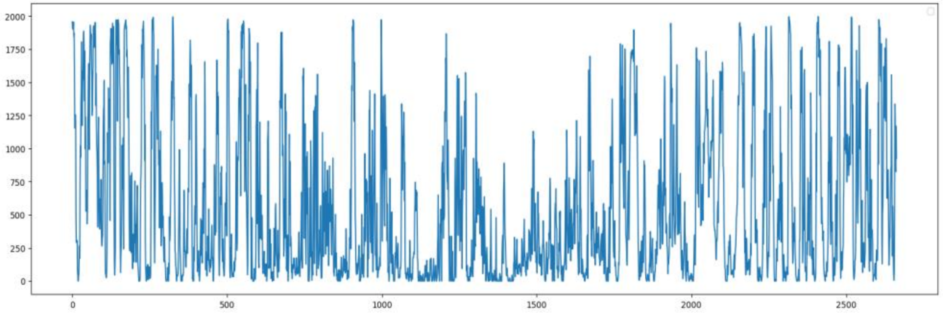
Introduction

Renewable energy 2030 plan



- The importance of **renewable energy**, such as solar and **wind power**, is **growing** in efforts to achieve carbon neutrality and RE100.

- Renewable energy generation is highly variable,
  → **Accurate** generation **forecasting** is important for **effective** power supply **planning**
- In this study, we aim to **interpret** the forecasting model trained with a **Transformer** architecture.



Wind power generation in 1 year (2017)

Energy Plan: Ministry of Trade, Industry and Energy. Republic of Korea 2017

Dataset

Wind Power Generation Data

- 01.01.2014 ~ 31.12.2017 (4 years)
- Wind generation : Recorded every 10 minutes
- Location : Sungsan wind power plants at the east coast in Jeju island, South Korea

Data source of wind power plants

Weather Forecast Data

- 01.01.2014 ~ 31.12.2017 (4 years)
- Weather forecast : Announce starts at **2 am**
- Announce every 3 hours ($t = 2, 5, 8, 11, 14, 17, 20,$ and 23)
- Total 8 time-zones

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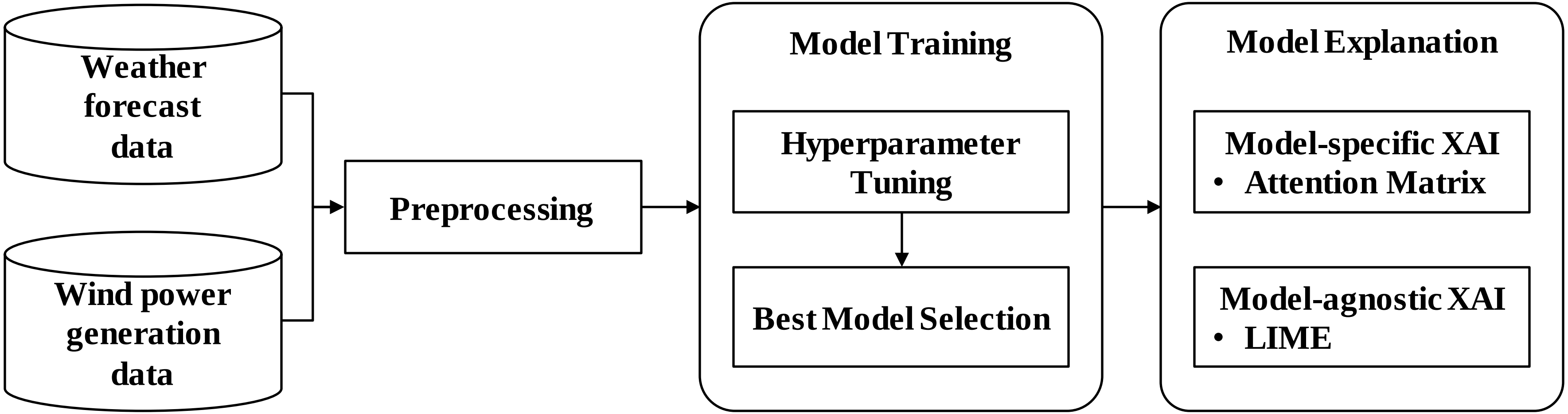
Korea Meteorological Administration

Data source of weather forecast:
Korea Meteorological Administration (KMA)

“Combined two datasets at 3-hour intervals. 8 samples for every day”

Framework

- **Procedure for the train and explanation of wind power forecasting models using Transformer architecture (WindTransNet)**



Train of WindTransNet

Towards G

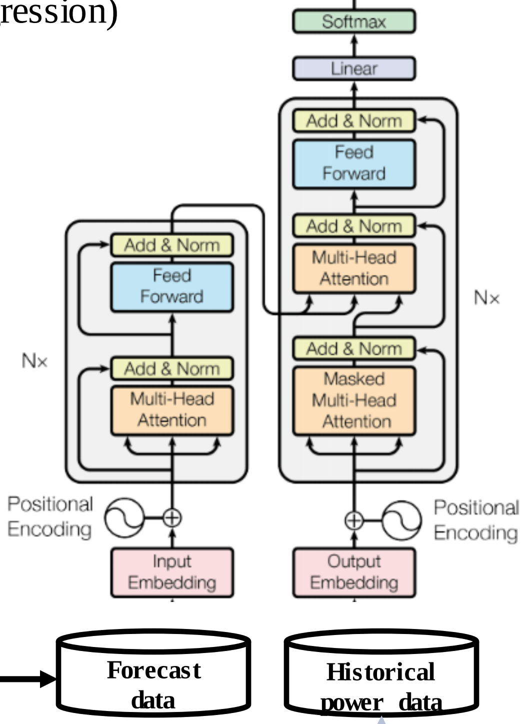
- **Wind power forecast model based on weather forecasting and historical power generation**
  - Goal : to predict average wind power generation per 1 day (multi-step regression)

Output
(8-step regression)

Power Generation	
Time	Date time
t+1	15/02 /2014 02:00
…	…
t+6	15/02 /2014 17:00
t+7	15/02 /2014 20:00
t+8	15/02 /2014 23:00

(5 days)	Weather Forecast Data	
	Time	Date time
d – 3	t–31	11/02 /2014 02:00
…	…	
d	t–7	14/02 /2014 02:00
	…	…
	t–2	14/02 /2014 17:00
	t–1	14/02 /2014 20:00
	t	14/02 /2014 23:00
d+1	t+1	15/02 /2014 02:00
	…	…
	t+6	15/02 /2014 17:00
	t+7	15/02 /2014 20:00
	t+8	15/02 /2014 23:00

(5 days)	Historical Power Generation Data	
	Time	Date time
d – 4	t–39	10/02 /2014 02:00
…	…	
d – 1	t–15	11/02 /2014 02:00
	…	…
	t–10	13/02 /2014 17:00
	t–9	13/02 /2014 20:00
	t–8	13/02 /2014 23:00
d	t–7	14/02 /2014 02:00
	…	…
	t–2	14/02 /2014 17:00
	t–1	14/02 /2014 20:00
	t	14/02 /2014 23:00



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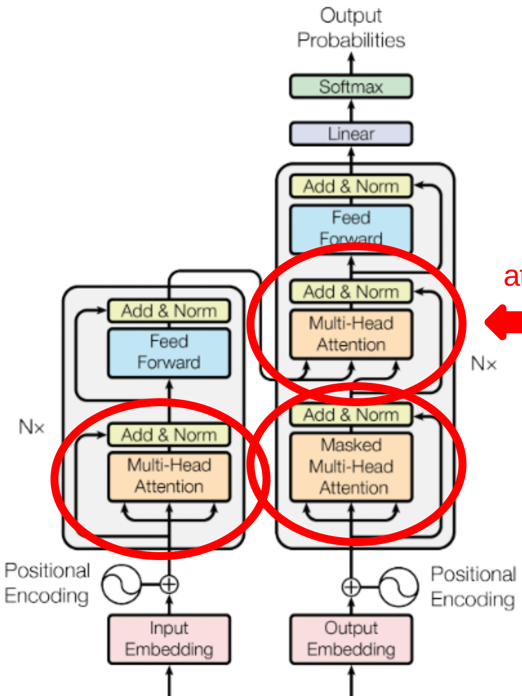
Explanation of WindTransNet

- We focus on the **Multi-Head Attention** in the second sub-layer in the decoder.
- Because it allows to verify the **relationship between the decoder's input and the encoder's input**, and
- **the attention represents the final learning stage** for generating the outputs (before the fully connected layer).



cross
attention

(5 days)	Time	Date time
	Weather Forecast Data	
d – 3	t–31	11/02 /2014 02:00
...	…	
	t–7	14/02 /2014 02:00
	…	…
d	t–2	14/02 /2014 17:00
	t–1	14/02 /2014 20:00
	t	14/02 /2014 23:00
	t+1	15/02 /2014 02:00
	…	…
d+1	t+6	15/02 /2014 17:00
	t+7	15/02 /2014 20:00
	t+8	15/02 /2014 23:00

X

(5 days)	Time	Date time
	Historical Power Generation Data	
d – 4	t–39	10/02 /2014 02:00
...	…	
	t–15	11/02 /2014 02:00
	…	…
d – 1	t–10	13/02 /2014 17:00
	t–9	13/02 /2014 20:00
	t–8	13/02 /2014 23:00
	t–7	14/02 /2014 02:00
	…	…
d	t–2	14/02 /2014 17:00
	t–1	14/02 /2014 20:00
	t	14/02 /2014 23:00

Results – Forecasting of WindTransNet

- **Four wind power forecasting models**
  - LSTM: the improved recurrent neural network used for handling sequential data
  - at-LSTM: the model that combines the **LSTM** with the **Attention** mechanism
  - WindTransNet-E: the transformer model using **an encoder without a decoder**
  - **WindTransNet-EDH (proposed):** the transformer model using **both an encoder and a decoder**

Performance of four wind power forecasting models

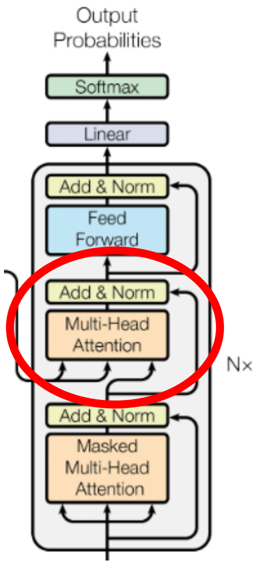
Wind forecasting model	RMSE		MAE		R^2	
	valid	test	valid	test	valid	test
LSTM	452.78	464.08	313.29	324.21	0.36	0.33
at-LSTM	467.22	474.47	319.36	332.65	0.32	0.30
WindTransNet-E	475.82	475.04	319.19	323.24	0.30	0.30
WindTransNet-EDH (proposed)	**452.51**	**440.76**	**305.40**	**300.96**	**0.36**	**0.39**

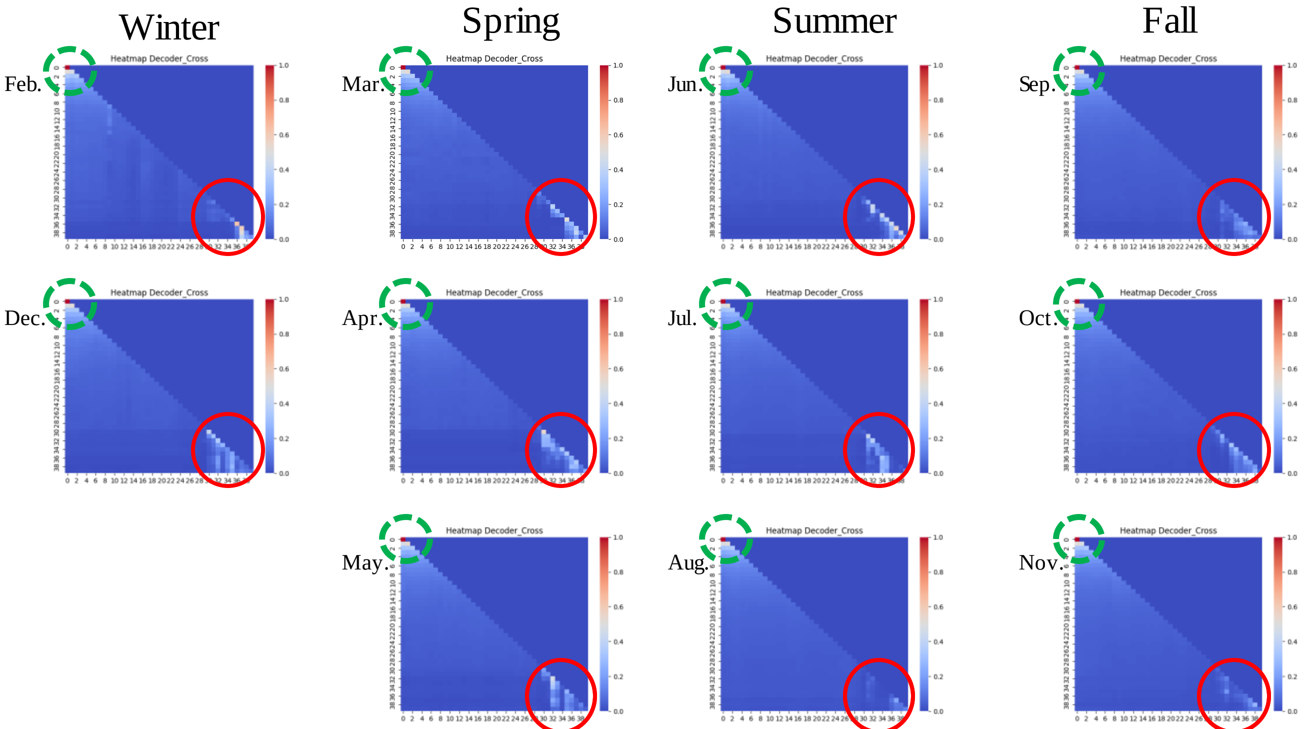
Hyperparameter tuning of WindTransNet-EDH

Hyperparameter	Search space
Time lag	$lag \in \{1, 3, \mathbf{4}, 5, 7, 14, 30\}$
Num. of layers	$l \in \{1, \mathbf{2}, 4\}$
Num. of heads	$h \in \{\mathbf{2}, 4, 8\}$
Learning rate	0.001
Batch size	16
Optimiser	AdamW
Dropout	0.2
Max epochs	10,000
Loss function	MAE

Results – Explanation of WindTransNet

- We focus on the **Multi-Head Attention** in the second sub-layer in the decoder.

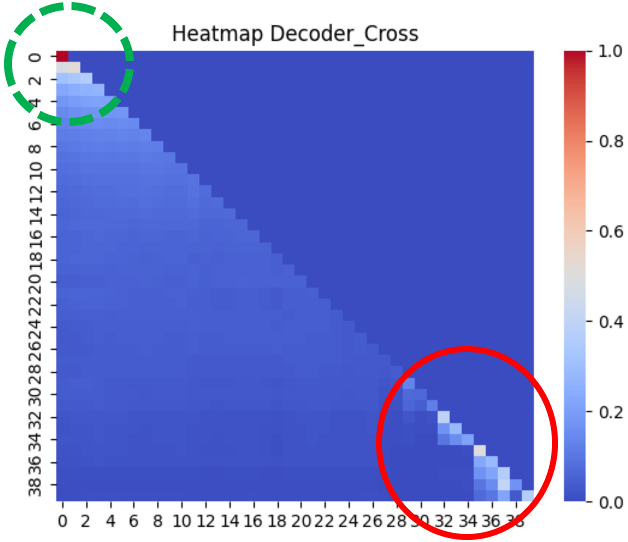




Explanation - Attention

Attention matrix in Spring (17.03.01)

March



Background

- Horizontal axis: Forecast data
  day–4, day-3, …, day_0
- Vertical axis: Historical data (generation)
  day–5, day-4, …, day_1

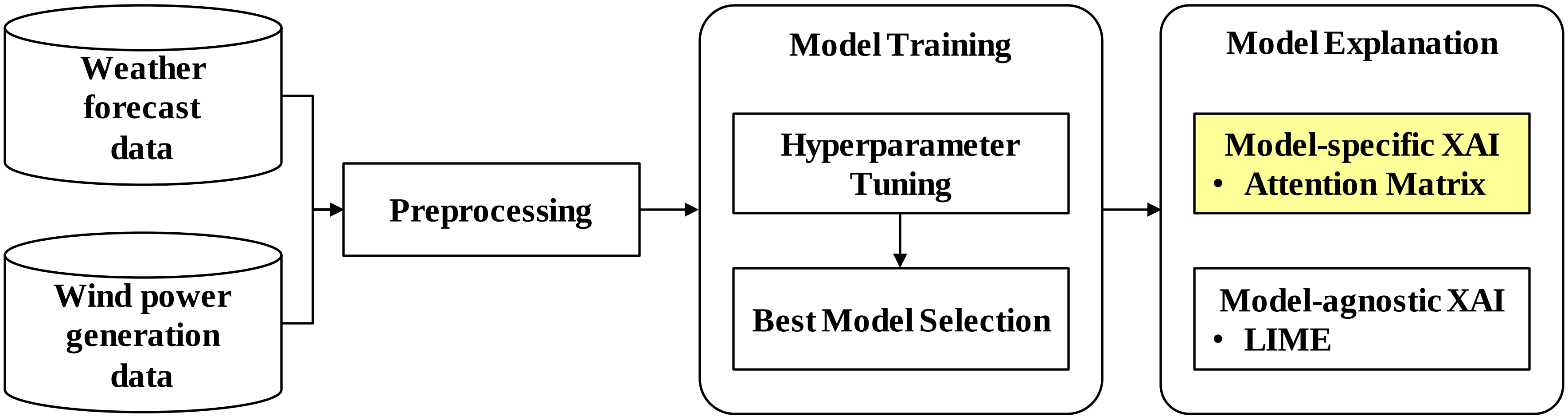
Explanation

- First, red section in the bottom right,
  we can see that when the transformer performs inference at that specific time, the multi-head attention focuses on the recent time step.

- Green section in top left, the red box has the highest value.
- Recall that the y-axis represents past data.
- Since the generation data does not change drastically, the transformer references the initial generation values and pays less attention to the subsequent ones.

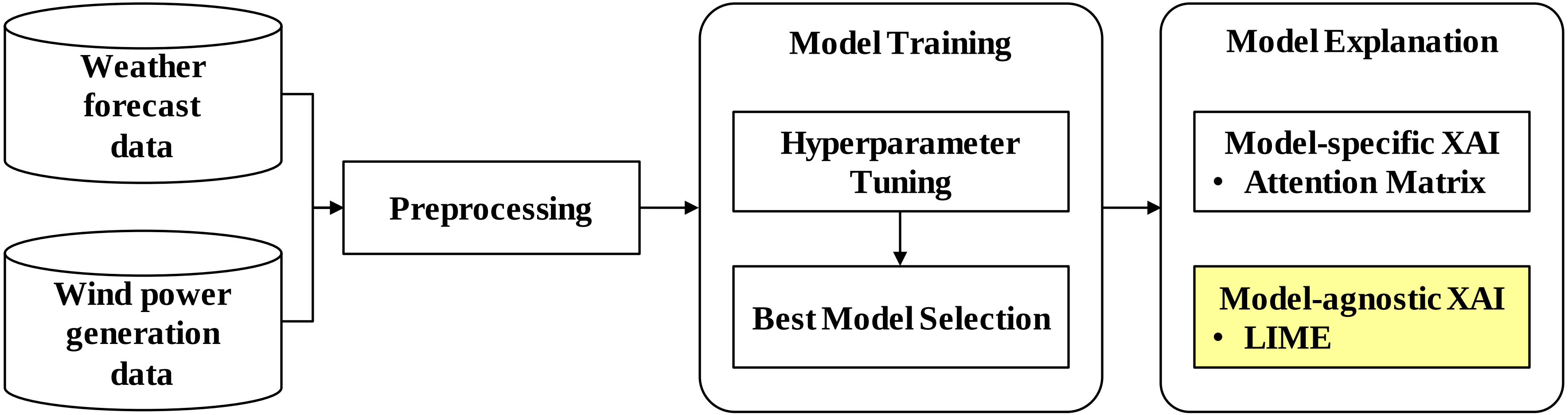
Explanation - Attention

- **Two Types of Explainable AI Methods**



Explanation - Attention

- **Two Types of Explainable AI Methods**



Explanation - LIME

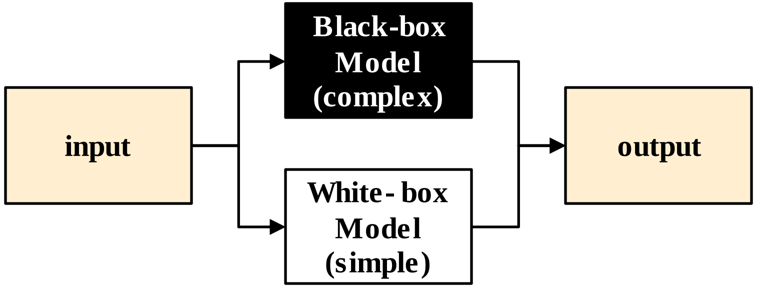
Local
Interpretable
Model-agnostic
Explanations

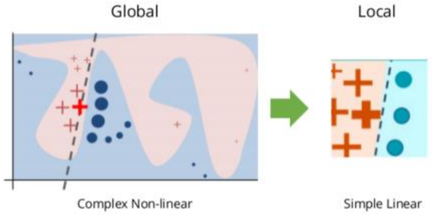
Model Explanation

Model-specific XAI
- **Attention Matrix**

Model-agnostic XAI
- **LIME**

- LIME trains a white-box algorithm, like a linear model, on the local decision boundary of the main model.
- This white-box model is called a surrogate model, and its coefficients are used to interpret the original black-box model.





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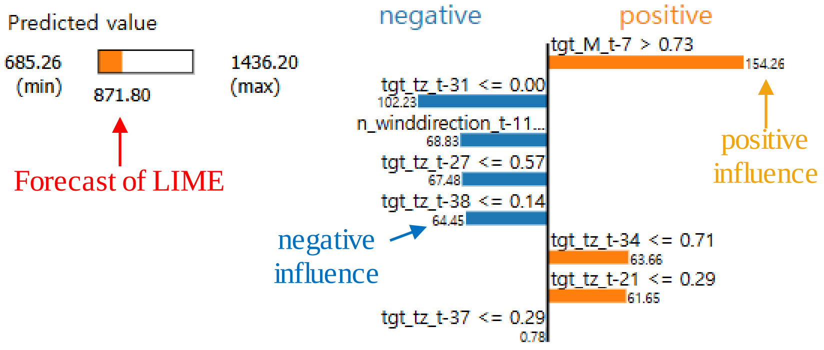
Explanation - LIME

[**High** power generation case] Time: 16.12.2017 15:00

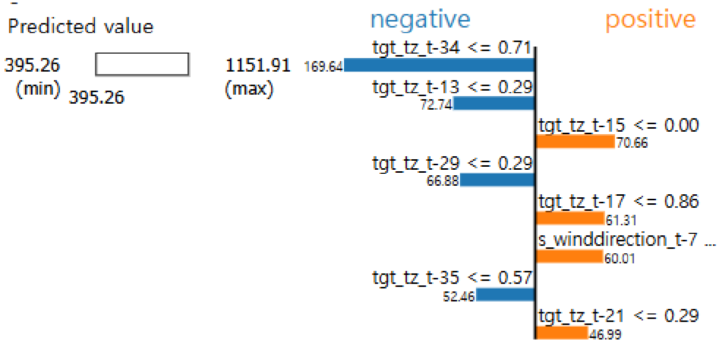


Bar chart

Feature	Value
tgt_M_t-7	1.00
tgt_tz_t-31	0.00
n_winddirection_t-11	0.89
tgt_tz_t-27	0.57
tgt_tz_t-38	0.14
tgt_tz_t-34	0.71
tgt_tz_t-21	0.29
tgt_tz_t-37	0.29

Actual feature values

[**Low** power generation case] Time: 28.06.2017 15:00



Bar chart

Feature	Value
tgt_tz_t-34	0.71
tgt_tz_t-13	0.29
tgt_tz_t-15	0.00
tgt_tz_t-29	0.29
tgt_tz_t-17	0.86
s_winddirection_t-7	0.32
tgt_tz_t-35	0.57
tgt_tz_t-21	0.29

- The first figure represents the forecast of the LIME model.
- The right table shows the actual values of features.
- In the bar chart, the **orange** bar indicates a **positive** influence in LIME's explanation, while the **blue** bar does a **negative** influence.
- [tgt_tz] and [wind_direction] appear frequently, which means that these features had significant impacts on the power generation forecasting.

Conclusions

- We first trained wind power generation forecasting models using Transformer model, and then interpreted the model using the explainable AI such as a model-specific method (Attention Matrix) and a model-agnostic method (LIME).
- The Transformer model, WindTransNet-EDH, demonstrated excellent predictive performance compared with other forecasting models.
- Attention Matrix visualized how the model learned the relationship between weather forecast and historical generation data.
- LIME was used to analyze the impact of individual features on the prediction, enhancing model transparency.
- Explainable AI techniques increase model reliability and enhance the potential for real-world applications.

References

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Thank You