Probabilistic Wind Power Forecasting

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INTRODUCTION

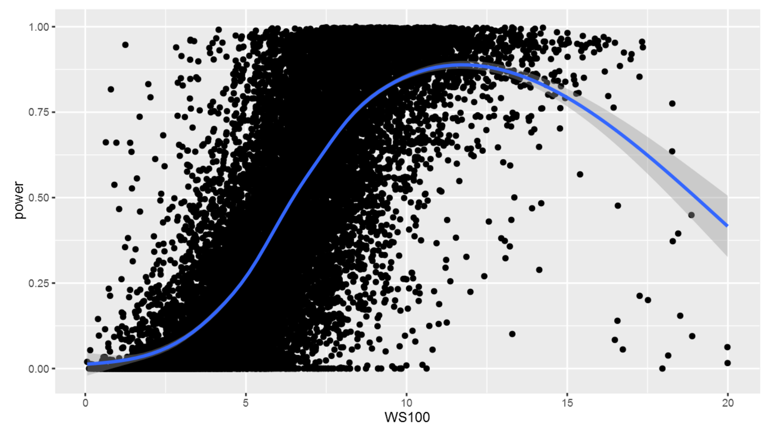
- Machine learning has become an effective tool for interpretation and prediction in real-life tasks involving large data sets.
- Renewable energy industries are interested in estimating the energies consumed and produced in a future time period based on historical trend.
- Compared to point forecasting, probabilistic forecasting gives more comprehensive information about future events by assigning probabilities to each outcome.
- Data are provided by CrowdANALYTIX GEFCOM 2014 with raw inputs of zonal(U) and meridional(V) components of the wind speed, timestamp as well as the observed wind power output.

OBJECTIVES

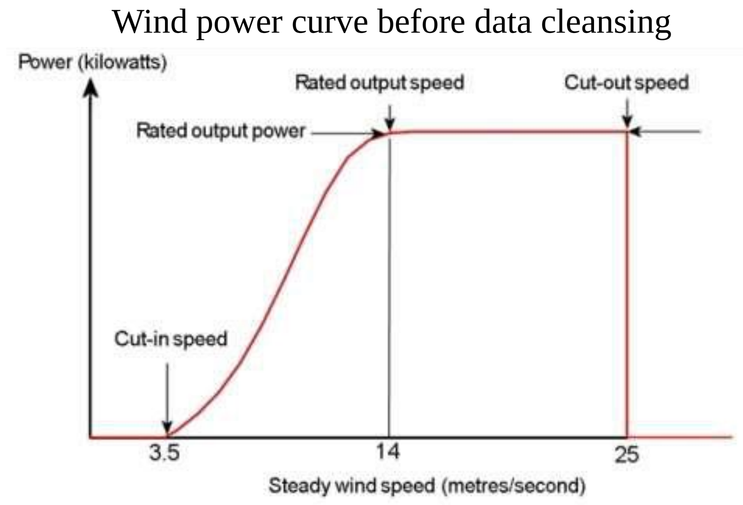
- ***Forecast*** the probabilistic distribution(in quantiles) of the wind power generation based on history input data.
- ***Replicate*** using some of the famous methods from published work.
- ***Explore*** and apply some of the newest machine learning algorithm(R packages).
- ***Compare*** with published results to seek improvements and deficiencies.

DATA CLEANSING

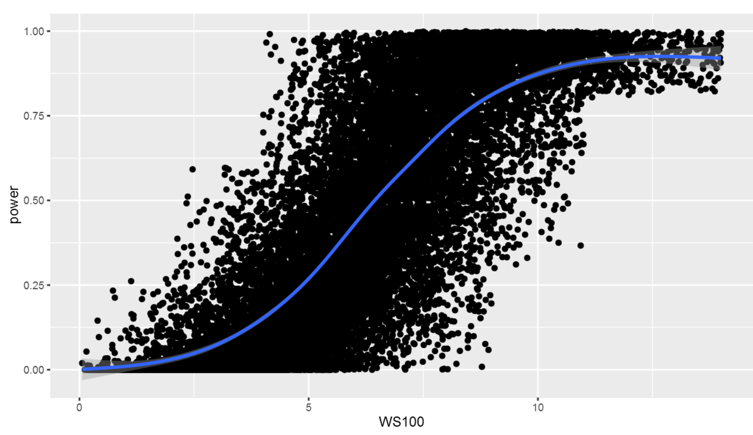
- ***Exclude*** time periods which have power equals to 0 continuously for more than 48 hours.
- ***Omit*** time spots where responding power is not defined(NA).
- ***Remove*** outliers according to the theoretical relation.



Wind power curve before data cleansing



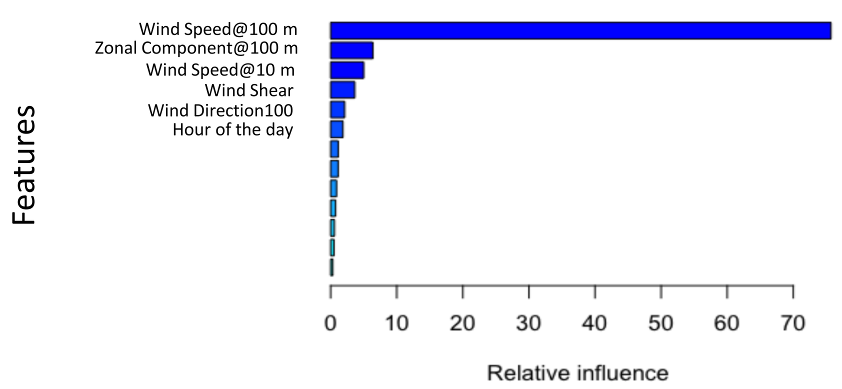
Theoretical relation between wind power and speed



Wind power curve after data cleansing

FEATURE SELECTION

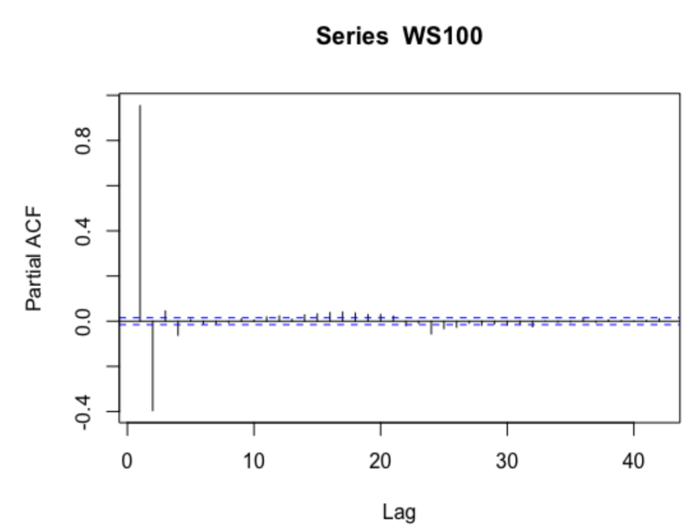
- Tool: Build-in feature importance function in Gradient Boosting Machine(GBM)



- Wind speed: $\sqrt{U^2+V^2}$
- Wind direction: $\frac{180}{\pi}\tan^{-1}(U,V)$ or $\frac{180}{\pi}\tan^{-1}(U,V)+360$
- Wind shear: $|WS100-WS10|$
- Hour: $\cos(\frac{2\pi * Hour}{24})$

LAGGED VARIABLES

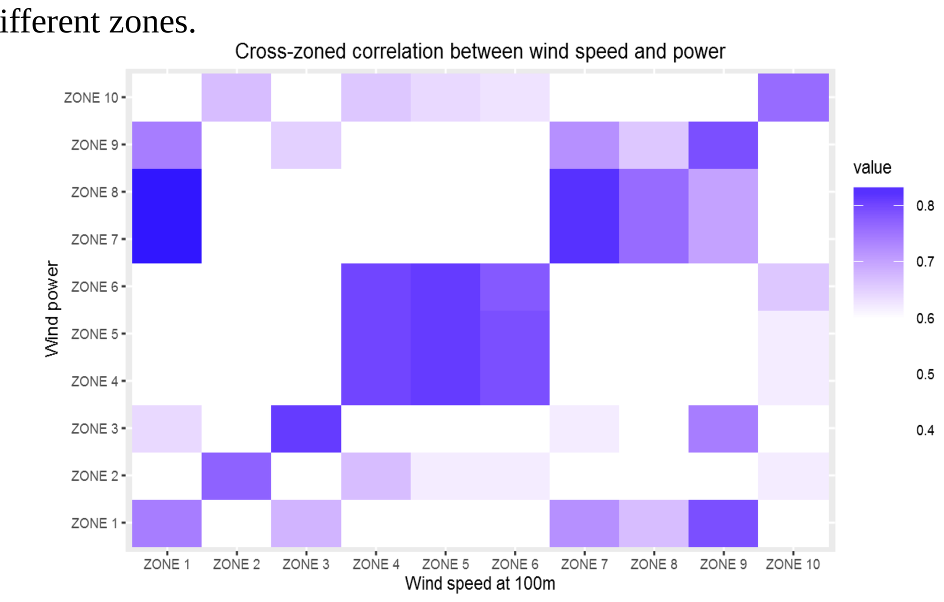
- Lagged variables are almost always considered in time series analysis for better prediction due to the time-dependent nature of the data. Original inputs are shifted by selected time units to form lagged variables.
- Tool: Auto correlation function(acf) in R.



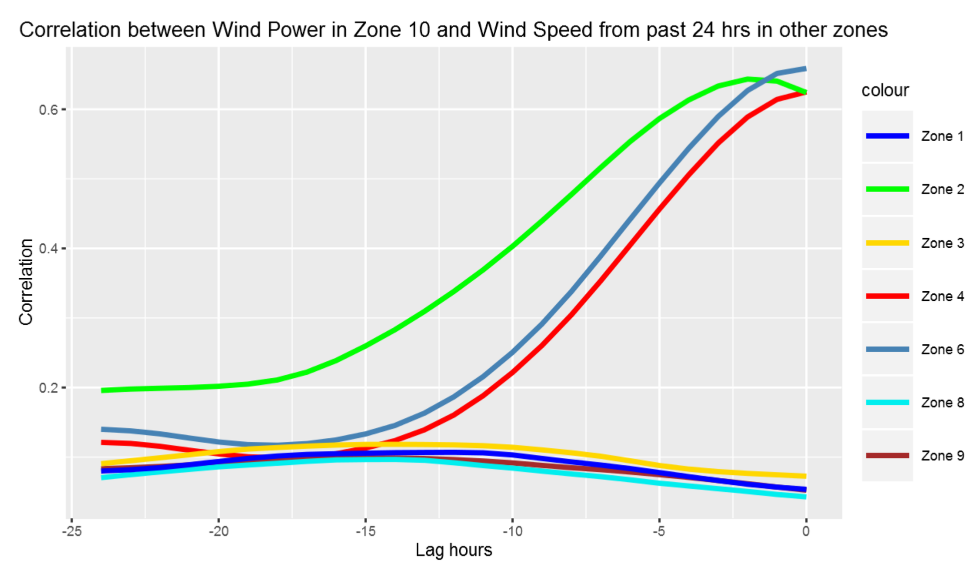
- Correlation is peaked between WS_t and WS_{t-1}.

Zonal Correlation

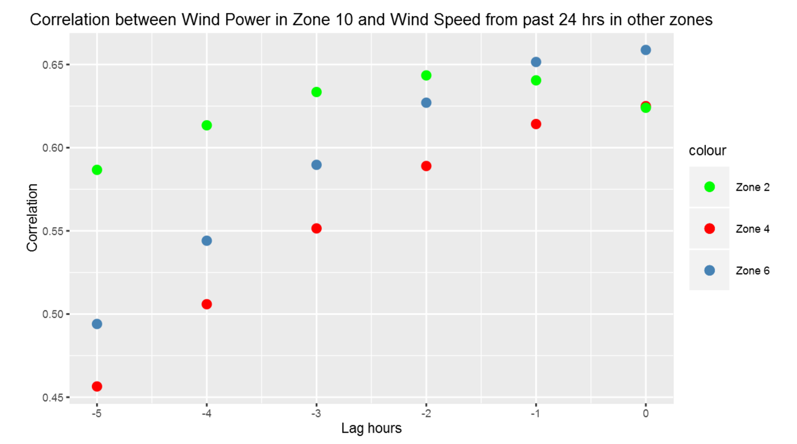
- Wind farms in this task are located in the same region of global, therefore it is intuitive to think that there might be cross correlation between different zones.



- Darker region infers higher cross-correlation



- Zone 2, 4, 6 have the highest correlation with zone 10. In general, high correlation is reached starting from t-3.

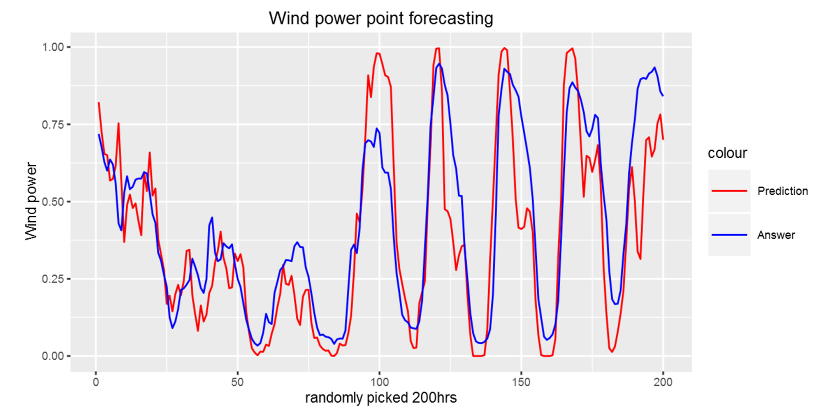


POINT FORECASTING

- Tool: eXtreme Gradient Boosting(XGBoost), a variant of GBM but much faster.
  1. A loss function to be optimized
  2. A weak learner to make predictions(Decision trees)
  3. An additive model to add weak learners to minimize the loss function
  4. Learn a regression predictor -> Compute residuals -> Learn to predict the residuals -> Adds up to the original model -> Repeat

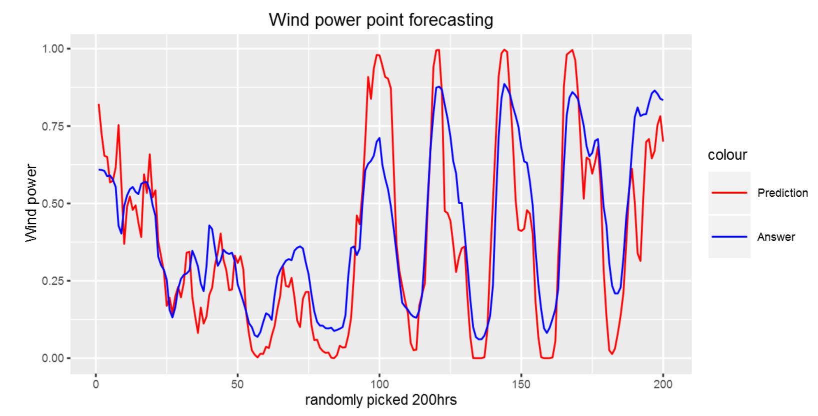
GBM

MSE: 0.02588



XGBoost

MSE: 0.02352

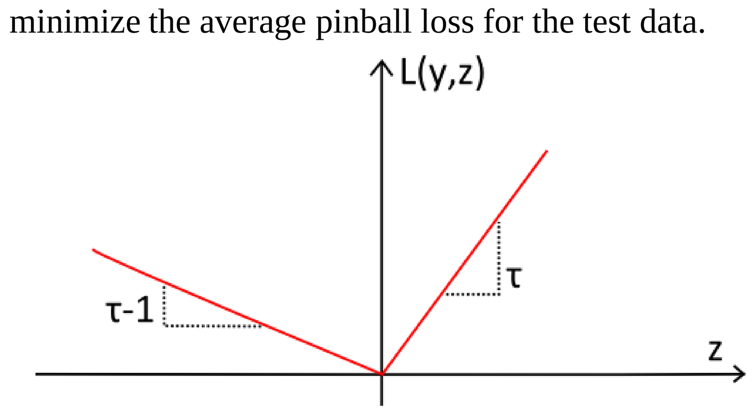


PROBABILISTIC FORECASTING

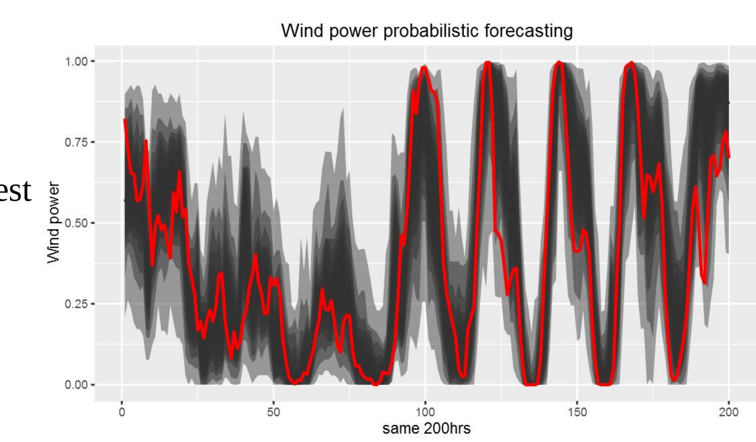
- Tool: GBM with built-in quantile regression; quantregForest
- Similar to point forecasting, but use quantile loss(pinball loss) instead of squared loss.
- Pinball loss function
  1. Let τ be the target quantile, y the real value and z the quantile forecast. Then $L\tau$, the pinball loss function, can be written as:

$$L_\tau(y,z) = \begin{cases} (y-z)\tau & \text{if } y \geq z \\ (z-y)(1-r) & \text{if } z > y \end{cases}$$

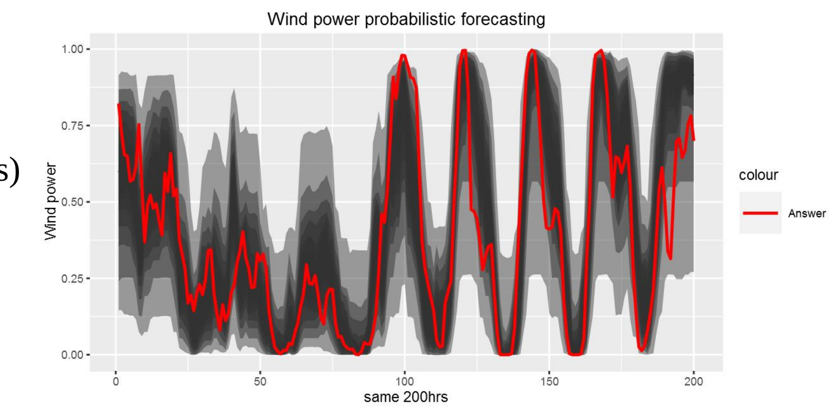
- We want to minimize the average pinball loss for the test data.



quantregForest



GBM(quantile loss)

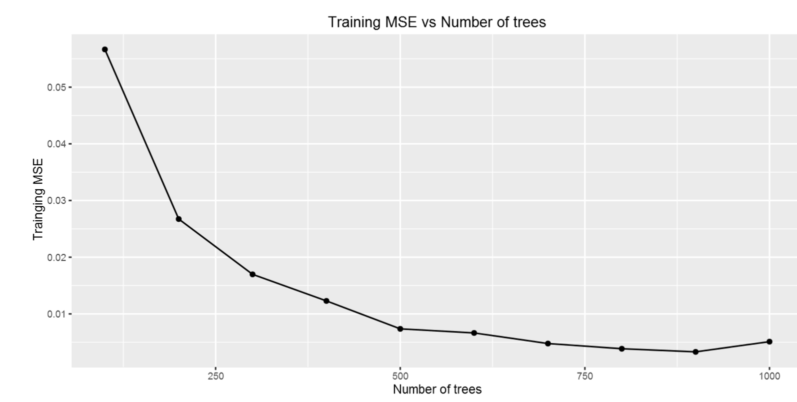


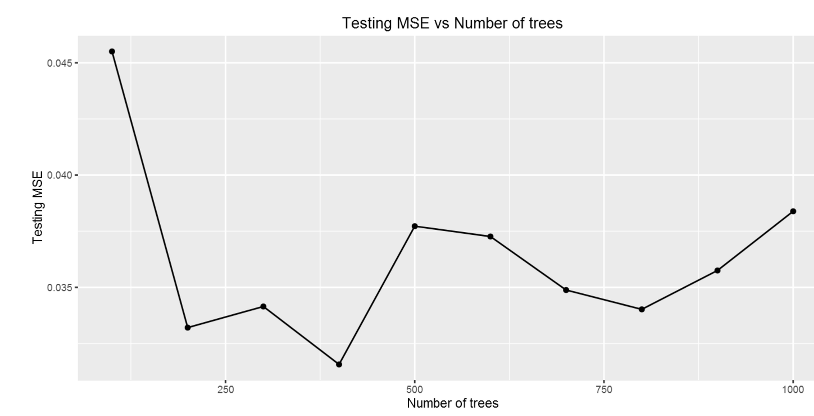
Models	Bench mark	quantregForest	GBM (quantile)
Pinball loss	0.07584	0.06373	0.03452

- Bench mark was given by GEF2014 by assigning constants to each quantile

PARAMETER TUNING

- GBM and XGBoost have lots of tunable parameters
- Regular cross validation and bootstrapping: problematic
- Possible mistakes: use future data to predict history data, inconsecutive sample data
- Choice: self-designed validation process





- We seek value of parameter that gives both low training error(bias) and testing error(variance).

CONCLUSION AND EXPANSION

- The combination of XGBoost as point forecasting model and GBM (quantile loss) as probabilistic forecasting model gives a very impressive forecasting score.
- Parameter tuning can be done more sophisticatedly
- More interesting packages to be explored: MXNet, QRNN
- Possible reason for zones with same input but different outputs might be the difference in wind turbine
- Periodicity of wind speed, wind direction etc. can be taken in to consideration as some published work suggested.

RESOURCES AND REFERENCES

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2. Zhang, Yao, Jianxue Wang, and Xifan Wang. "Review on Probabilistic Forecasting of Wind Power Generation." *Renewable and Sustainable Energy Reviews* 32 (2014): 255-70. *Review on Probabilistic Forecasting of Wind Power Generation*. Elsevier, 31 Jan. 2014. Web. 16 Dec. 2016.

3. Probabilistic Forecast Application in Power Systems – Yi Luan, Bolun Xu University of Washington