PREDICTING WIND ENERGY PRODUCTION WITH SCIKIT-LEARN

• INTRODUCTION

Nowadays, electricity networks of advanced countries rely more and more in non-operable renewable energy sources, mainly wind and solar. However, in order to integrate energy sources in the electricity network, it is required that the amount of energy to be generated to be forecasted 24 hours in advance, so that energy plants connected to the electricity network can be planned and prepared to meet supply and demand during the next day (For more details, check "Electricity Market" at Wikipedia).

This is not an issue for traditional energy sources (gas, oil, hydropower, …) because they can be generated at will (by burning more gas, for example). But solar and wind energies are not under the control of the energy operator (i.e. they are non-operable), because they depend on the weather. Therefore, they must be forecasted with high accuracy. This can be achieved to some extent by accurate weather forecasts. The *Global Forecast System* (GFS, USA) and the *European Centre for Medium-Range Weather Forecasts* (ECMWF) are two of the most important Numerical Weather Prediction models (NWP) for this purpose.

Yet, although NWP's are very good at predicting accurately variables like "100-meter U wind component", related to wind speed, the relation between those variables and the electricity actually produced is not straightforward. Machine Learning models can be used for this task.

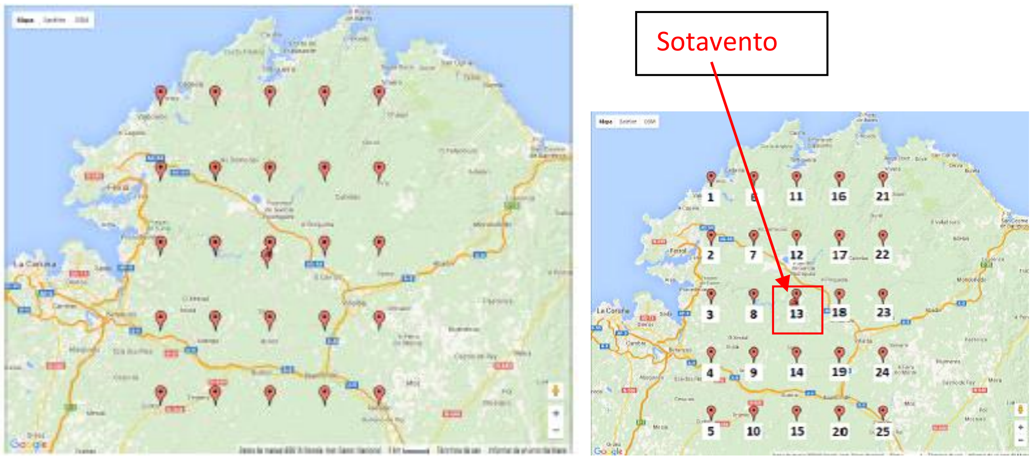
In particular, we are going to use meteorological variables forecasted by ECMWF (http://www.ecmwf.int/) as input attributes to a machine learning model that is able to estimate how much energy is going to be produced at the Sotavento experimental wind farm (http://www.sotaventogalicia.com/en).

Sotavento wind farm.

More concretely, we intend to train a machine learning model *f*, so that:

- Given the 00:00am ECMWF forecast for variables $A_{6:00}$, $B_{6:00}$, $C_{6:00}$, … at 6:00 am (i.e. six hours in advance)
- $f(A_{6:00}, B_{6:00}, C_{6:00}, \ldots)$ = energy = electricity generated at Sotavento at 6:00

We will assume that we are not experts on wind energy generation (not too far away from the truth, actually). This means we are not sure which meteorological variables are the most relevant, so we will use many of them, and let the machine learning models and attribute selection algorithms select the relevant ones. Specifically, 22 variables will be used. Some of them are clearly related to wind energy production (like “100 metre U wind component”), others not so clearly (“Leaf area index, high vegetation”). Also, it is common practice to use the value of those variables, not just at the location of interest (Sotavento in this case), but at points in a grid around Sotavento. A 5x5 grid will be used in this case.



5x5 grid around Sotavento.

Therefore, each meteorological variable has been instantiated at 25 different locations (location 13 is actually Sotavento). That is why, for instance, attribute iews appears 25 times in the dataset (*iews.1, iews.2, …, iews.13, …, iews.25*). Therefore, the dataset contains 22*25 = 550 input attributes.

GENERAL CONSIDERATIONS:

1. Results must be reproducible. Therefore, set the seed at the appropriate places. But instead of using seed 42, use the NIA number of one of the members of the group.
2. There are two datasets, the available data set (for model training, hyper-parameter tuning, and model evaluation) and the competition dataset (for using the model: making predictions for future instances).

3. Execution time of the training processes should also be reported.

WHAT TO DO:

1. (0.4 points) Explore your data and do a **simplified** EDA, mainly in order to determine how many features and how many instances there are, which variables are categorical / numerical, which features have missing values and how many, whether there are constant columns (that should be removed), and whether it is a regression or classification problem (energy is the response variable). You might want to explore other issues you find interesting, but bear in mind that in this assignment EDA is only 0.4 points.
2. (0.3 points) Decide how you are going to carry out the outer evaluation (estimation of future performance) and the inner evaluation for comparing different alternatives. Decide which metric you are going to use. Provide justifications.
3. (4.7 points) Main body of the assignment. The Sotavento company wants you to get some conclusions about the following issues. In order to come up with a conclusion, you will need to experiment with different alternatives and compare them with the inner evaluation.

a. (0.3 points) The following issues need not be dealt with in that order, nor be systematic. Please, provide an initial plan about the order in which you are going to explore these issues (although you can change your plan later).
b. (0.6 points) Tell how you have used ChatGPT in this assignment. You can describe a summary of your experience with ChatGPT in the context of the assignment, important prompts you have used, some cases where you found out that ChatGPT was wrong, etc. No more than 3 pages in the report.
c. (0.3 points) Are all the 550 attributes really necessary? Maybe only the attributes related to the Sotavento location (13^{th} location in the grid) are actually required? Or only the attributes related to wind? (you are not expected to use automatic feature selection techniques here, rather, select features by hand)
d. (0.4 points) Does imputation improve performance in this problem? Which method seem to work best?
e. (2.6 points) Which method is more appropriate to the problem? (among trees, KNN, and two ensemble methods). Does hyper-parameter tuning contribute to improve performance? At what cost (compute time). Which HPO method does perform better? (among Random Search, Optuna, and Halving Search).
f. (0.5 points) Try something on your own: a new library, explore an issue you are interested in, etc.

1. (0.6 points) Once you have decided on the best alternative (based on comparing different alternatives using the inner evaluation):
    a. Using the best alternative (based on inner evaluation), make an estimation of the accuracy that the final model might get on future data (outer evaluation).
    b. Train the final model and use it to make predictions on the “competition data”. Save both the final model and the competition predictions on files.

WHAT TO HAND IN:

- One or several jupyter notebooks. Please, use some of the cells to make comments about what you are doing and your results. Also, try to justify your decisions. If your group has two members, please write your names at the beginning of the notebook. You can also hand in a file with Python code, and a separate report, if it is more convenient to you.
- A file containing your final model.
- A text file containing the predictions of final model.

- Please, submit just one zip file. Don’t forget to write the names of the two members in the code and the report.

APPENDIX: ATTRIBUTE NAMES:

- t2m: 2 metre temperature
- u10: 10 metre U wind component
- v10: 10 metre V wind component
- u100: 100 metre U wind component
- v100: 100 metre V wind component
- cape: Convective available potential energy
- flsr: Forecast logarithm of surface roughness for heat
- fsr: Forecast surface roughness
- iews: Instantaneous eastward turbulent surface stress

- inss: Instantaneous northward turbulent surface
- lai_hv: Leaf area index, high vegetation
- lai_lv: Leaf area index, low vegetation
- u10n: Neutral wind at 10 m u-component
- v10n: Neutral wind at 10 m v-component
- stl1: Soil temperature level 1
- stl2: Soil temperature level 2
- stl3: Soil temperature level 3
- stl4: Soil temperature level 4
- sp: Surface pressure
- p54.162: Vertical integral of temperature
- p59.162: Vertical integral of divergence of kinetic energy
- p55.162: Vertical integral of water vapour