Active multiple kernel learning of wind power resources

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Abstract

Wind power resources in mountainous regions are conditioned on a vast variety of factors influencing air flow. Complex topography causes various phenomena such as localised thermal winds, acceleration due to tunneling and Foehn winds interfering at a range of spatial scales and varying in time due to weather seasonality. It increases the dimensionality of parameter space and adds additional complexity to sampling strategies and monitoring network design for wind resource assessment and location allocation for wind turbines. This work explores an active learning approach to multiple kernel learning (MKL) to explore the high-dimensional space of topographic features influencing wind speeds. MKL allows handling spatial heterogeneity and non-stationarity while providing physically interpretable data-driven models useful for decision support. Our results on real data from the Swiss Alps suggest the efficiency of MKL both for feature selection, predictive modelling and sampling design, also showing that care has to be taken to avoid over-fitting by over-localised terms in kernel dictionaries.

1 Introduction

Increase of the share of renewable energies in countries power gross consumption is one of the challenges for energetic efficiency in the future. After the events in Japan in 2011, Switzerland has set as a priority to decrease the recourse to nuclear energy and to gradually switch to green energy resources, with the objective to give up nuclear power in 2050. One of the most appealing solutions is windpower, as windfarms are efficient and do not require large ground coverage as photovoltaic panels and do not imply large facilities, as water energy does. If the massive recourse to the first is difficult because of the mountainous topography of Switzerland, the second is unlikely, since most of the valleys suitable to dams have already being exploited or are protected national parks.

To increase the recourse to windpower, new windfarms must be planned thoroughly. Selection of a site goes through a difficult phase of public consultancy, but must also meet production criteria stated in the Swiss Law. In the Bylaw on Energy (Ord 730.1[1]) it is stated that wind power plants must be constructed in sites showing an average wind speed exceeding 4.5 [m/s] at a height of 50 [m] above the ground, with an estimated roughness length of 0.1 [m]. Moreover, wind plants must keep a productivity of 100-150%. Keeping these facts in mind, the planning of new wind plants must monitor wind speed over time to ensure enough speed and wind constancy. Therefore, maps of average winds are useful documents when deciding on the suitability of a site for the construction of a plant. In this optic, prediction maps must be as accurate as possible. To ensure efficient modeling, we study the multitemporal behavior of windspeed in mountainous Switzerland by underlying the areas meeting the 4.5 [m/s] requirement between 2003 and 2008 using SVM. To account for complex topography, we extracted topographical indices and performed weighted feature selection using multiple kernel learning [1, 2, 3]. By considering single variable settings and grouped settings, we assessed the importance of the different parameters to learn the complex problem of wind speed.

[1] Available at www.admin.ch/ch/f/rs/c730_01.html

Once the windfarm suitability map has been produced, we also considered increasing the confidence and accuracy of the estimation. Assuming a new measuring station can be added to the sensor network, the new station could be located as a function of the objective that is being optimized, i.e. the fulfillment of the 4.5 [m/s] requirement for new plants. For this purpose, we exploited active learning algorithms [4] to assess the confidence of the prediction over the six year sequence. To do so, we used the margin sampling criterion proposed by Schohn and Cohn [5]. By considering distribution of the uncertain samples in terms of topographical properties, guidelines for priorization for location of new measuring stations are given.

2 Data

We consider time series $2003-2008$ of average monthly wind speeds measured by the Swiss monitoring network, which is composed of 130 measuring stations on the Swiss territory. The Swiss Digital Elevation Model (DEM) at a resolution of (250×250) [m^2] was used to extract 13 features: (as in [6]):

- Spatial coordinates (X, Y) (features 1 and 2) and altitude (Z) (feature 3),
- Difference of Gaussians (DoG, features 4-6). By subtracting two smoothed DEM surfaces obtained with different smoothing bandwidths, the ridges and canyons of different characteristic length scales are highlighted. The resulting set of features describes terrain convexity at three different spatial scales (small, medium and large),
- Slope (features 7-9). The norm of the terrain gradient, which is proportional to slope, is computed on smoothed DEM surfaces at three spatial scales as well. Terrain slope is expected to explain the lower wind speeds in the flanks of inner Alpine valleys,
- Directional derivatives (DD, features 10-13). These features highlight natural obstacles represented by relief, that break winds by being perpendicular to its direction. They could also describe patterns of wind shadowing with respect to the predominant mesoscale winds. In summer they could potentially explain some thermal effects due to sun exposure. Zero values occur in flat regions (North-South, East-West).

Topographic features are extracted both on the DEM grid and at the location of meteorological stations. The final input space is a 13 dimensional vector.

3 Learning meaningful topographic features with MKL

The problem of assessing suitability of a site to host a windfarm is casted as a classification problem. All stations data are used to classify the monthly wind speed $\bar{s}_{50}$. The positive class is given when $\bar{s}_{50} > 4.5$ while the negative when $\bar{s}_{50} < 4.5$. This value is given by an average model for Switzerland, that extrapolates the speed at 50 [m] by using the speed at 10 [m] (height above the ground of the stations) using the a simple linear conversion factor.

We studied the contribution of topographic features by constructing linear kernel combinations [3] in two settings: first considering a feature per kernel (left panel of figure 1) and then building separate kernels for each source of information in the list above (right panel of figure 1). In both cases, single kernel parameters were assessed using kernel alignment [7]. In both cases, the importance of altitude and DoG features, underlying the canyoning effects, can be clearly seen and the directional derivatives are highlighted in the optimization by groups, showing that joint consideration of features in kernels can lead to more meaningful description of the phenomenon under study. Figure 2a illustrates the results of the 72 months analysis. Areas in bright tones fulfill almost always the requirements in different months and years, while areas in black never fulfill them. This map brings multitemporal information about persistence of winds at the necessary speed for correct functioning of wind power plants and can constitute a useful document for renewable resources assessment.

4 Active learning of wind farms location

In order to improve the decision map in Fig. 2a, new measurement stations could be added to represent the topographic conditions where the spatial classification of wind speed is most uncertain. The question of the location of such stations remains open and we tackle it here through active learning.

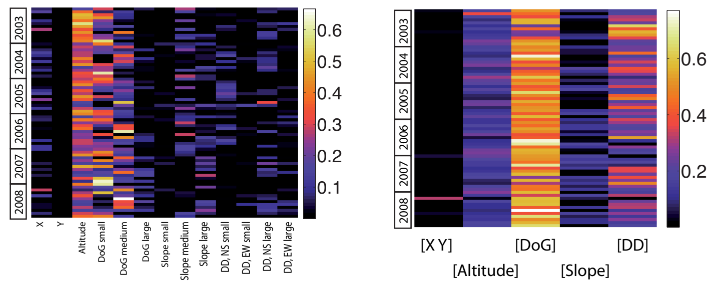
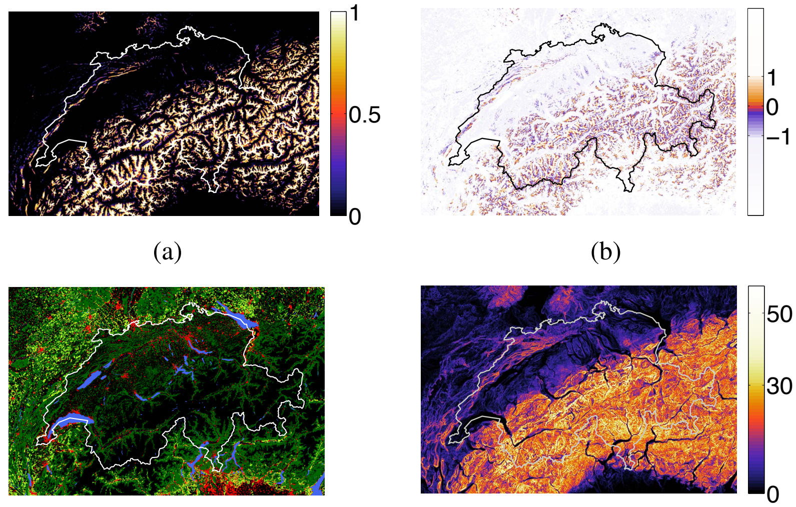


Figure 1: Weights learned by MKL. Left: single features. Right: aggregation of multiscale features.

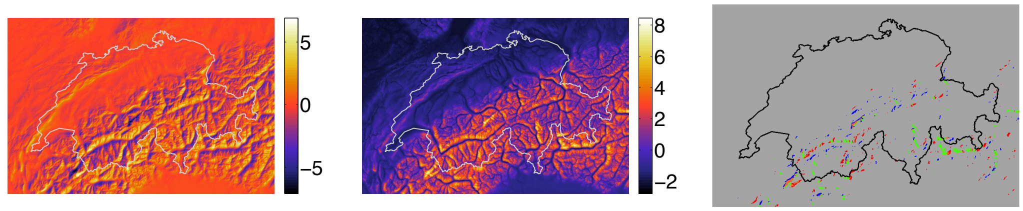


(a) (b) (c) (d)

Figure 2: (a) frequency of suitability for wind power production in the 2003-2008 period; (b): mode of the distribution of distances to the hyperplanes for the classification of $w_{50} > 4.5$ [m/s] constrained by landuse and slope. Strong colors denote areas of uncertainty of the predictions (c) distribution of landuse types unsuitable for windfarm installation (in black, suitable areas); (d) distribution of slopes (in dark tones, suitable areas).

Large margin models also provide information about the confidence of the class assignment, by the decision function of the SVM [5]. Using such confidence, we can detect the topographic situations which are underrepresented by the current sensor network for the specific task of wind speed modelling. We will focus on uncertain areas with respect to the modelling of the boundary defining the areas where winds are close to 4.5 [m/s], that is within the margin of SVM. An increase in precision of the definition of these areas can have enormous impact on decision making processes. Figure 2b illustrates the confidence of the class assignments over the 72 months, measured as the mode of the single decision functions, constrained by i) areas where windfarms cannot be bulilt (figure 2c) and ii) too steep areas ($> 30°$, figure 2d). The areas in red / violet tones are those of frequent reduced confidence in the class assignment.

To select the new potential sampling sites, we extracted the uncertain regions (with mode of the decision function in [-1;1]) and analyzed the recurrent topographical conditions in these pixels. We performed PCA to extract general trends. The two components related to maximal variance (left and central panel of Fig 3) underline high slope regions (PC1 and PC2), with strong directional derivatives (right tail of PC1 and of PC2) and of high altitude (right tail of PC2). The interest on slope jointly with directional derivatives is interesting, and denotes the insufficient variability of the samples for these phyisical parameters that make the MKL model ignore them in the overall prediction. Such analyses confirm the well-known underrepresentation of Alpine slopes by the MeteoSwiss network and the uncertainty of renewable energy assessment in complex Alpine environments. Using



1^{st} PC, 18% of total variance 2^{nd} PC, 17% of total variance   Decision map

Figure 3: Analysis of topographic features of the retrieved principal components. Left: map of DEM projected on the most informative principal component; middle: projection on the second most informative component; right: decision map based on the tails of the two principal components retained (Blue: sites related to left tail of PC1; red: sites related to right tail of PC1; green: sites related to right tail of PC2; orange: common sites, sampling priorities.).

this information and taking into account diversity of the topographical conditions, new monitoring stations for wind speed with increased diversity can be installed.

5 Conclusions

In this study, we assessed the power of recent machine learning advances for the assessment of renewable energy potential. We considered wind power, which is one of the most suitable and promising resources for the green-energy policy of the near future in Switzerland. Multitemporal analysis has been carried out for the search of potential sites for wind power farms. The integration of topographical information has shown desirable properties, also evaluated by the analysis of kernel weights of the multiple kernel classifier deployed. To increase confidence in the estimation, the design of the weather monitoring network has been analyzed and a feedback loop using active learning has been designed to focus new measurements sites on the areas of uncertainty of the model. The results show a clear underrepresentativeness of topographical information related to exposition and slope. Stations located in the specific areas highlighted could improve general knowledge about winds in complex topographical area and decrease uncertainty on the site design model developed, thus providing more reliable products for decision making in energy policies for the next years.

Acknowledgments

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