Electricity Price Forecasting with Deep Neural Networks

Electricity is a *basic human need* and definitely one of the most important factors of societal progress. In recent decades however, electricity has entered the market as a tradeable commodity and the power industry of many countries has been **deregulated**. In Spain, the Electric Power Act 54/1997 exposed all of the stakeholders to **high amounts of uncertainty** as the price of electricity is determined by countless factors and also, due to the fact that electricity cannot be stored in large quantities efficiently [1]. With the emergence of this new market, the need for reliable forecasting methods at all scales (hourly, daily, long-term, etc.) has also emerged and has become a large area of research.

The goal of this kernel is to compare different **deep neural network architectures** (+XGBoost) on the task of **predicting the next hour's electricity price** by using the past values of the electricity price as well as those of another features related to energy generation and weather conditions. Furthermore, the kernel contains a meticulous *exploration and cleaning* of the data, *time series analysis* of the electricity price and careful *feature engineering*. With further research and development (e.g. as a forecasting model which is updated in real-time) a similar approach could possibly prove useful to all the stakeholders (electric power companies, investors, etc.) involved in energy markets. For the time being, I believe that this kernel can serve as a **future reference** for aspiring data scientists, as it contains an *end-to-end time series forecasting project* and demonstrates the -minimum- level of immersion that a dataset needs in order to turn into something which is actually applicable in the real world.

In the **original project**, which was conducted for a postgraduate course, I compared the performance (using the Root Mean Squared Error as the performance metric) of 5 different architectures (LSTM, stacked LSTM, CNN, CNN-LSTM and Time Distributed MLP) for both univariate and multivariate forecasting (i.e. using only the previous time-steps of the electricity price vs. also using other features) using a different number of previous time-steps as the features for the models (3, 10 and 25 previous time-steps for all the used features). In **this particular kernel**, you will find an application of all the aforementioned deep le

arning architecures, as well as two more approaches: the *Encoder-Decoder* architecure and the *XGBoost regressor*. Furthermore, in all these applications, I use the 25 previous time-steps of all the features (multivariate forecasting) that have been extracted or generated, after applying *PCA (Principal Component Analysis)*. The **Adam optimizer** is used in all the deep learning architectures and, in order to choose its learning rate, I originally conducted preliminary tests using the the *learning rate scheduler* callback starting from a learning rate equal to 0.0001 and gradually increasing it by a factor of 10 every 10 epochs; a step which is omitted in this kernel.

The information that we have about the weather of 5 major cities in Spain (highlighted by a red star on the map below) is probably more than enough for our analysis, since their geographic distribution covers most of the part of Spain's territory in a uniform manner. Moreover, it is useful to note that these 5 cities alone comprise approximately 1/3rd of the total population of Spain.