Title: Development of geophysical monitoring Machine Learning techniques for real-time prediction of parametric variations associated with CO_2 storage activities in geological reservoirs.

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Proposal *The geological storage of CO_2 is currently considered as one of the main tools for reducing carbon dioxide emissions into the environment and preventing climate change. Geophysical methods in the field of CCS (Carbon Capture and Storage) is of fundamental importance for monitoring and interpreting the evolution of the reservoir and for assessing any critical issues. Through the interpretation of 4D geophysical data it is in fact possible to remotely trace the development and evolution of the CO_2 plume and provide fundamental information to mitigate the potential risks of leakage. Most of the current studies, however, are based on the development of multiphysics simulations which, as the degree of complexity of the site increases, require considerable capacities and calculation times as well as information on the temporal variations of numerous physical parameters. This PhD project aims, therefore, at the definition of new geophysical monitoring and forecasting tools through the development of Machine Learning techniques, which are able to solve non-linear problems of considerable complexity through self-learning mechanisms. A Supervised Learning type system will be adopted, where the training phase of the model will be conducted through the generation of synthetic time-lapse geophysical datasets based on realistic multiphysics simulations. These techniques will be applied to geophysical datasets generated at different time intervals for the real-time prediction of the spatial and temporal parametric variations associated with CO_2 storage activities.*

Research Program

First of all, the PhD student will have to develop a storage simulation phase within geological reservoirs. These simulations will be conducted based on the available reservoir properties (e.g. porosity, permeability, depth, temperature, pressure, structural elements) at regular time intervals, as well as assuming different operating information, such as the injection rate and injection/post-injection times. In this way, a series of potential reservoir models will be carried out, representing all the possible geological scenarios, that is all combinations of reservoir properties that cannot be excluded from the available geological knowledge. These models are then used to estimate the geophysical responses at each time step. The models provided by the simulations and the related geophysical datasets will be used to develop the training phase of the neural networks, which will be trained to recognize the output (the 'data labels') both of numeric type (e.g. saturation level) and of category (e.g. predisposition to leakage), through the *physical relationships that link the parametric variations to the time-lapse geophysical data. Given the size of the problem, Convolutional Neural Networks (CNNs) will be used, such as the ResNet (Residual Neural Network) algorithm, whereby fewer parameters need to be stored, thus reducing model memory requirements and improving its efficiency.*

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