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Crossed studies of causal attribution for complex systems:
The case of climate change

Climate is a very complex system being affected by the behavior a great number of highly interacting subsystems (atmosphere, biosphere, hydrosphere, cryosphere, anthroposphere, etc.). This is why it is very difficult to manage the climate crisis relying exclusively on scientific knowledge. To deterministically forecast the future trend of a complex system like climate is impossible, but detecting the causes of a complex phenomenon is easier, even if not conclusive either in this case. To deal with this uncertainty, climate scientists community developed a multilateral approach, carrying out a sort of "crossed" study of causal attribution performed by methodologically different tools: *computational models*, *neural network* techniques and *statistical analysis*.

The standard approach to climate forecasts involves the use of computational models like AOGCMs (General Circulation Atmosphere-Ocean Models) used by the IPCC (Intergovernmental Panel on Climate Change). These models are made by sets of parameterized differential equations that combined with initial conditions reproduce Earth's behavior simulating the interactions between atmosphere, oceans, cryosphere and biosphere as well as the impact of human activities on climate. These are extremely useful, but not perfect instruments to deal with complexity. Petersen (2006) detected a number of sources of uncertainty: in the *conceptual* model (e.g.: holistic versus reductionist approach), in the *mathematical* model (model structure and parameterization), in model *inputs* (data and scenarios), in *technical implementation* (software and hardware) and in *output data* (interpretation and communication). Causal attribution studies performed through mathematical models clearly shows that it's impossible to forecast current values of global mean temperature without introducing anthropogenic forcing, namely *carbon dioxide*, *methane* and *nitrous oxide* concentration in atmosphere.

Likely, despite being so complex, climate system has been widely studied so that now we have a huge amount of data about past dynamics of relevant variables like temperature, humidity, solar irradiance, greenhouse gases concentration in atmosphere, etc. Pasini, Ameli, Lorè (2006) tried to use these "big data" to overcome the complexity due to non-linear interactions without succumb to the temptation of reductionism by using neural networks, computational devices inspired to human brain architecture made by simple memory units (*neurons*) linked together through weighted connections (*synapses*). Like brain, the net can "learn" from experience: feeding the device with data in input and output (e.g.: global mean temperature in 1850 and global mean temperature in 2000) the weights of links change to better fit the relation between initial and final conditions. When a certain degree of stability in these values is observed, the training phase is complete; now the network knows the function which goes from input to output data and it's ready to provide highly reliable results. So, while climate models reconstruct the evolution of the entire system starting from how its components, neural networks simulate the behavior of Earth as a whole allowing a more holistic look to its dynamical evolution. Providing a neural network with the huge amount of available data about past temperatures and past level of greenhouse gases we obtain a weighted net by which Earth's evolution can be simulated without recurring to the mathematical description of subsystems behavior. Actually, as mathematical models, neural networks are not able to reconstruct current temperatures without taking into account the human influence.

Statistics too provide good techniques to work with "big data". Using the notion of *Granger-causality* (Granger (1969)), Attanasio, Pasini, Triacca (2012) performed a different analysis of causal attribution detecting a clear signal of linear Granger-causality from greenhouse gases to the global temperature of the second half of the 20th century, while Granger-causality has not be found to be evident using time series of natural forcing like solar irradiance, cosmic ray intensity and stratospheric aerosol optical thickness. It is important to point out that Granger-causality is stronger than simple statistical correlation: in fact, we say that a variable X is Granger-cause of the trend of a variable Y if the knowledge of past values of X significantly improve the forecast of values assumed by Y.

Climate sciences provide just a case study of this multilateral strategy but, in my opinion, this crossed analysis could be also useful in the study of other complex systems behavior, not only in causal attribution, but also in forecasting process.

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