Causal Reasoning in Machine Learning

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Current Machine Learning Limitations

Thanks to recent advancements in Artificial Intelligence (AI), we are now able to leverage Machine Learning and Deep Learning technologies in both academic and commercial applications. Although, relying just on correlations between the different features, can possibly lead to wrong conclusions since correlation does not necessarily imply causation. Two of the main limitations of nowadays Machine Learning and Deep Learning models are:

- Robustness = trained models might not be able to generalise to new data and therefore would not be able to provide robust and reliable performances in the real world.
- Explainability = complex Deep Learning models can be difficult to analyse in order to clearly demonstrate their decision making process.

Developing models able to identify cause-effect relationships between different variables, might ultimately offer a solution to solve both of these problems. This idea, has also been supported by researchers such as Judea Pearl, which advocated how having models able to reason in uncertainties could not be enough to enable researchers to create machines able to truly express intelligent behaviour [1].

Concepts of Causality

Nowadays Machine Learning models, are able to learn from data by identifying patterns in large datasets. Although, humans might be able to perform a same task after just examining a few examples. This is possible thanks to the inherit humans ability to understand causal relationships and use inductive inference [2] in order to assimilate new information about the world [3]. Creating models able to demonstrate causal reasoning, would therefore open to us a whole new world of opportunities in AI research. Causality arises naturally in our daily life every-time we ask ourselves any type of interventional or retrospective question (eg. What if I take this action? What if I would have acted differently?). As shown in Figure 1, Causal Reasoning can be divided in three different hierarchical levels (Association, Intervention, Counterfactuals). At each level, different types of questions can be answered and in order to answer questions at the top levels (eg. Counterfactuals) are necessary as basis knowledge from the lower levels [4]. In fact, in order to be able to able to answer retrospective questions, we would expect to first be able to respond to intervention and association type of questions.

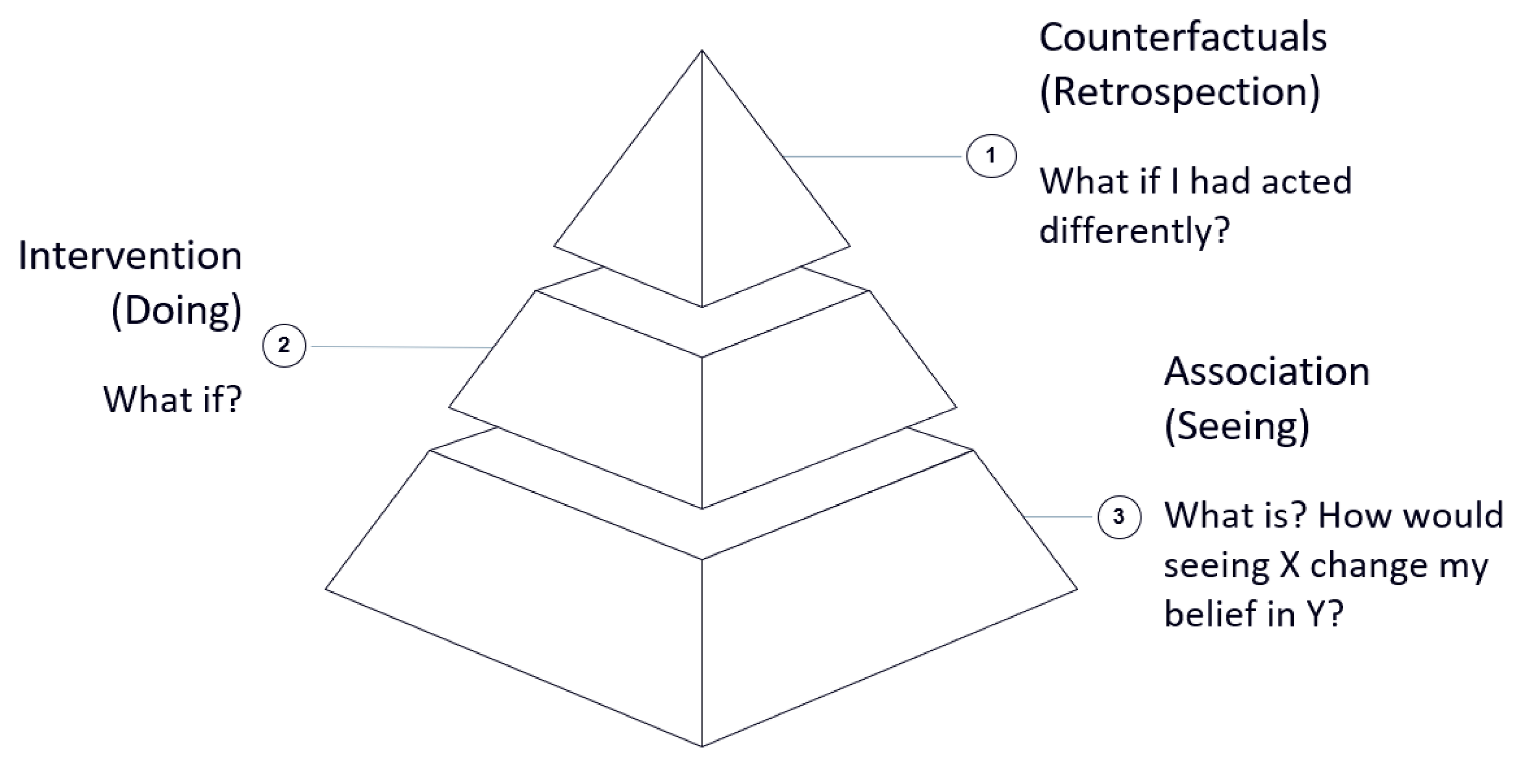

Figure 1: Causality Hierarchy

Currently, Machine Learning models are only able to answer the probabilistic type of questions related to the Association level.

Case Study

As case study for this project, will be ideated a modelling platform in order to make estimations about the development of epidemics following the basic principles of the epidemiologic triad (Figure 2) and modelling techniques such as the SIR model.

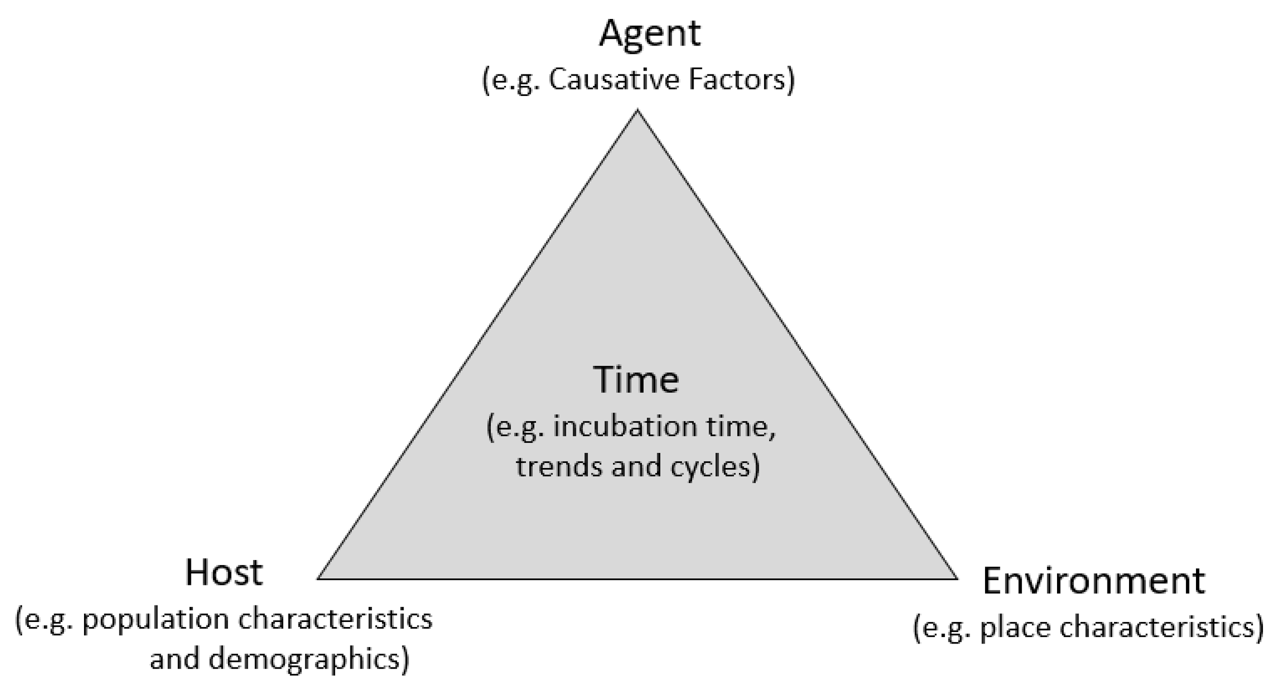

Figure 2: The Epidemiologic Triad

Using this platform, the user will be able to probe the model to provide estimates for questions like: How is putting in place a certain restrictive measure going to affect the spread of the disease? What are going to be their projected effects on the economy? How does varying the population size or the basic reproduction number affect the overall mortality rate?

Additionally, as part of this predictive tool will be included all the three different stages which characterises the spread of an infectious disease (Epidemic, Endemic and Eradication) and other data visualization techniques in order to provide additional insights.

Project Milestones

A simplified overall project workflow is summarised in Figure 3.

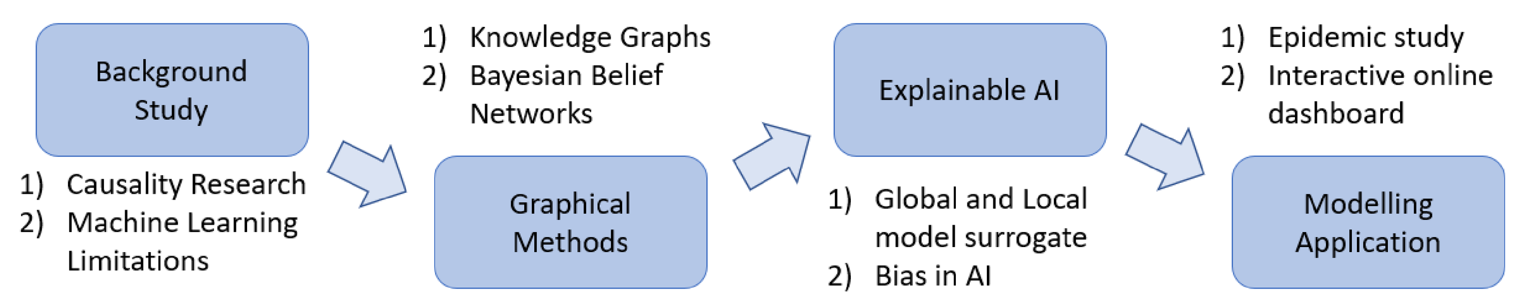

Figure 3: Block Diagram Plan

Why Causality Matters?

Successful introduction of causality in Machine Learning could lead to a wide adoption of the employed techniques (filling a market gap). Introduction of Causality in Machine Learning could moreover have important legal implications. In fact, use of Machine Learning in important decision-making applications is currently under probe by governments and institutions due to the risks involved. Enabling Machine Learning models to be more easily examinable to gain insights of their decision-making processes could in fact facilitate adoption of this kind of technologies in fields such as Medicine, Surveillance and Hiring. Although, before adoption, a series of benchmarking metrics should be instituted in order to ensure the reliability of any of the approaches proposed in this research study.

References

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