Causal Analysis with Applications to AI

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Causality is the most important discipline for artificial intelligence (AI)/machine learning (ML), even for the science. For instance, physics studies the causality of physics, chemistry studies the causality of chemistry, etc. In short, causality is the science of all science.

Before the rising of mathematical statistics, all the endeavor of scientists was aimed at the target of causality. However, the situation was changed when the concept of correlation came into the mind of statistician pioneers. Galton and his student K. Pearson introduced and popularized the method of correlation analysis, which led to many outstanding achievements in practice. Although it is known to everybody that correlation is not causal relationship, people still use the standards of goodness-of-fit in AI/ML research. Inevitably, some paradoxes came into being, confused the mathematicians many decades. They are alarm bells for the uncertain reasoning. As Judea Pearl, the winner of Turing award suggested, it is time to make the causality rigorous and rethink the cause-effects in AI paradigm.

This article “Causal Inference” is one chapter from my latest book, entitled by “Mathematical Foundations of Artificial Intelligence --- The Beauty of Randomness”, which will be published by Tsinghua University Press. The following is a brief introduction to this chapter.

The history background of causality is introduced in the preface, especially the thoughts of Hume and Laplace. Then the influence of Wright, Neyman, Fisher and Pearl is discussed. Confounding factor, the basic concept of causal inference, is explained by the story of “smoking causes lung cancer?” Simpson paradox may be the most famous example of causality. The importance of causality and causal graph is emphasized.

In the first section, intervention, as a critical approach to causal effects, is studied and formalized into adjustment formula, back-door criterion, front-door criterion. To make a complete causal graph (i.e., a sound story about the causal relationship), sometimes we need instrumental variable --- a bridge between given variables.

How to understand the data and the mechanisms of generating the data? Some examples are illustrated to show the necessity of causal modelling. Definitely, causal inference will improve the explainability of AI/ML.

Bayesian network is related to causal analysis, but they are theoretically different. Laplace originally explored the possible way from Bayesian to causal. Judea Pearl implemented his causality as Laplace wished. Some concepts for Bayesian network are extended to causal graph, for example, blocking, d-separation, etc.

To figure out the valid causal chain, mediation analysis is useful to solve Simpson paradoxes. In summary, intervention enable us to get the active observations, rather than passive ones.

The second section is about the counterfactual inference, which is seldom studied and applied in AI/ML. The probability of necessity and the probability of sufficiency are defined and utilized for counterfactual reasoning. Counterfactual ability is the essential part of intelligence. This direction will be very promising in statistics and AI/ML. The readers will find some detailed discussions on the application of causality to AI, including the history of AI, reflection on AI, ethics of AI, etc.

The third section introduces Laplace's causal inference from the Bayesian viewpoint. In particular, Laplace's probable cause and Laplace's approximate inference are shown. Several examples given by Laplace are further studied.

Since causal inference is still in development, there are lots of open problems in this domain. We are currently at the bottom of Pearl's ladder of causal relationship, where the strong AI is impossible to be achieved in neither theories nor applications. Therefore, intervention and counterfactual reasoning are becoming a matter of great concern.