

Causality in Neuroscience

An Annotated Bibliography

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This is what got us started in the topic. This is a seminar by Jan Peters consisting of four videos that gives us a really fun, accessible introduction to Causality. He is one of the authors of Elements of Causality book that we referred to in our seminar. We are kind of biased given that his origins are in Tuebingen :)

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Ferenc Huszar is a Machine Learning expert. In this series of his blog, he provides a very light and visual introduction

to causal inference, do-calculus, interventions, and counterfactuals. He nicely supports his explanations with graphics, simple examples, and small toy calculations.

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A recent review article by Konrad Kording and Iona Marinescu that pits theoretical (Pearl style) and empirical (ecometrics-based) techniques for determining causality against one another. {S: Konrad graciously accepted to come to Tuebingen and give a talk on Causal Neuroscience. He even gave us his material for this workshop. Kudos to him to be such a great sport.

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With his introduction of do-calculus, Judea Pearl became the father of the predominating mathematical framework for causality today. This book contains his theorems and teachings in a mathematically very rigorous manner. It might be very heavy on somebody who is new to the material, but it is

a very good reference for readers that are somewhat familiar with the causality.

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A really accessible introduction to Causality given by the father of Causality, Judea Pearl. Thank the editor Dana Mackenzie for making it an easy to read book.

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A study that shows reward prediction errors signalled by DA neurons form necessary and sufficient condition for learning associations.

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