Beyond the Horizon: Empirical Exploration of Opinion Dynamics via Inverse Modelling

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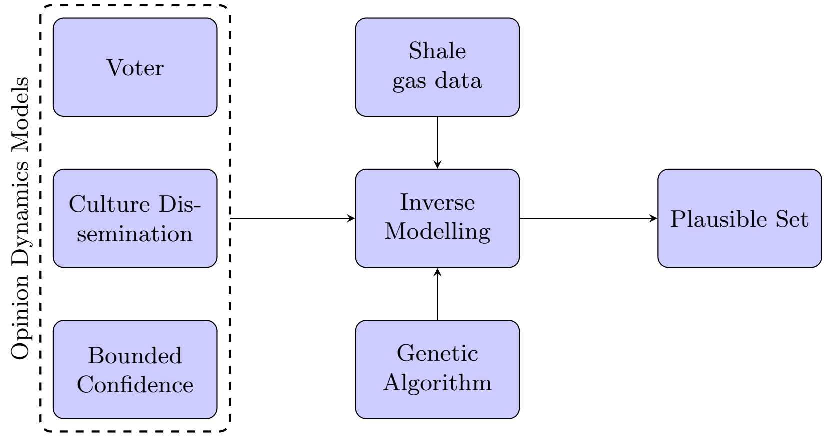
Polarisation is a complex social phenomenon pervasive in many of today's societal debates. Agent-based modelling (ABM) is a promising approach to capture the dynamics of polarisation in a simulated and controlled environment. However, developing ABMs that are grounded in empirical data can be challenging, particularly when data on the relevant factors driving polarisation are limited. The more mathematical theory opinion dynamics can be used to research on polarisation through models. However, the approaches seem to come short of empirical, data-driven validation, see, e.g., [4].

For this research, we propose to explore the use of inverse modelling to estimate the parameters of a data-driven agent-based model of polarisation using the well-known theory of opinion dynamics.

A comprehensive review of the research on opinion dynamics is presented, leading to the implementation of three "major streamlines" [4, p.76] of models: The Voter, Culture Dissemination, and Bounded Confidence model. These models are then tested for their ability to match and reflect existing-large scale data on polarisation.

1. The Voter model consists of agents on a two-dimensional lattice with their choice represented by a binary variable. Agents are influenced by their neighbours to change their voting behaviour to their neighbour's opinion [7].
2. The Culture Dissemination model (based on [1]) assumes a positive relationship between how likely individuals are to influence each other and the extent of cultural similarity between them. "Culture" here is a discrete vector and similarity measured by the Hamming distance.
3. The Bounded Confidence model attempts continuous opinion representation using the same assumption of the Culture Dissemination model, i.e., an agent only interacts with agents within a fixed boundary of difference in opinion, e.g., [3, 2].

We operationalise this as a case-study on the energy transition, using a data set on polarisation in the case of shale gas in the Netherlands, see [6]. The data consists of newspaper articles collected between 2010 and 2013, and a story line constructed complemented by interviews. The polarisation curve over time will be attempted to match using the opinion dynamics model.



The inverse problem is a methodology recently employed by ABM scholars as "inverse modelling", see [11, 8, 9, 10, 13]. Instead of meticulously designing an agent and observing which macro-patterns emerge, an agent is initialised and the parameters iteratively adjusted to match existing data and reproduce or approximate the phenomenon at hand. Conceptually, this approach is close to how neural networks naïvely operate, e.g., [5], so this topic is also receiving attention from the field of machine learning, e.g., [12].

Hopes are that this approach is not only more accessible to social researchers investigating transitions, but also allows for more data-driven, empirical approaches, and that through this, theories can be (case-specifically in-) validated and experimented with much easier.

With this, the research seeks to demonstrate the feasibility of using inverse modelling to develop data-driven agent-based models of polarisation.

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