Macroeconomic Agent Based Model Calibration using Iterated Surrogates

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1 Extended Abstract

Agent based models (ABMs) deal with the study of socio-ecological systems that can be properly conceptualized through a set of micro-macro relationships. The micro level typically contains basic heterogeneous entities that do not generally help explain the phenomena under study. In this context, one of the problems with ABMs is that the statistical properties of policy-relevant economic variables (e.g. inflation, GDP, employment) are *a priori* unknown, even to the modeler. These properties emerge indirectly from the repeated interactions among ecologies of heterogeneous, boundedly rational and adapting agents[2]. Therefore, the dynamic properties of the system cannot be studied analytically, the identification of causal mechanisms is not always possible and interactions give rise to the emergence of properties that cannot be simply deduced by aggregating those of micro variables (Anderson et al., 1972, Tesfatsion and Judd, 2006, Grazzini, 2012, Gallegati and Kirman, 2012). This raises the issue of finding appropriate tools to investigate the (macro) behaviour of the model with respect to different parameter settings, random seeds and initial conditions (Lee et al., 2015, see also). Once this analysis is carried out successfully, one can safely move to calibration, validation and, finally, use the model for policy exercises. Unfortunately, this procedure is hardly feasible in practice due to the expensive cost of computation.

Many ABMs simulate the evolution of a system for a relatively long time span, using relatively large sets of parameters. However, even for small models, exploring model behavior through a full factorial evaluation of all possible parameter combinations is practically impossible. This *Curse of Dimensionality* is a constraint even in the case of a low resolution grid over the parameter space. For example, consider a 5 parameter ABM and assume a single evaluation of the ABM costs 5 seconds on a single compute core (CPU). Discretizing the parameter space by splitting each dimension into 10 intervals would result in 10^5 evaluations and cost approximately 6 CPU days to explore. A finer partition of 15 intervals would result in 10^{15} evaluations and cost 1.5 CPU months. 20 intervals would require 6 CPU months and so on. Simply including a sixth parameter would require more than 10 years. These compute constraints deny policy-makers and regulators (e.g. FED or ECB) access to ABMs as part of their analysis. If a model is to be used by policy makers, it must provide timely

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[2]In the last two decades a variety of ABM have been applied to study many different issues across a broad spectrum of disciplines beyond economics and including ecology (Grimm and Railsback, 2013), health care (Effken et al., 2012), sociology (Macy and Willer, 2002), geography (Brown et al., 2005), bio-terrorism (Carley et al., 2006), medical research (An and Wilensky, 2009), military tactics (Ilachinski, 1997) and many others. See also Squazzoni (2010) for a discussion on the impact of ABM in social sciences.

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insight into the problem. As a result, gaining an intuition from models with rich expressiveness, but computationally expensive evaluations, is of limited practical interest. In this paper, we explicitly tackle the issue of exploring the parameter space of ABMs and calibrating two different ABMs according to two different policy constraints using real data. The approach presented also extends to the case of calibrating to wide or big data.

While computationally expensive simulation models are used to describe complex physical phenomena, surrogate models provide a fast (computationally cheap) proxy (approximation) for parameter-space exploration and calibration (see Booker et al., 1999). The resulting objective is to leverage the surrogate model in place of the simulator (ABM in our case) to considerably reduce computation time. The surrogate is then exploited to locate promising calibration values and convey an intuition over the parameter space to the practitioner (policy-maker). Given a small approximation error, the surrogate can be interpreted as an efficient and reasonably good approximation of the ABM. Here, a surrogate model is iteratively approximated over several rounds, as it learns to sample the parameter space, to maximize its performance in filtering positive calibrations from any out-of-sample set of parameters.

Traditionally, three computationally intensive steps are involved: running the agent-based model, measuring the calibration quality and locating parameters of interest. As remarked in Grazzini et al. (2015), such steps account for more than half the computation time required to estimate ABMs, even for extremely simple models[3]. We dramatically reduce the computational time by replacing the expensive ABM and calibration test with a nonparametric machine learning surrogate[4], that is, an efficient function approximation of the ABM with calibration test(s), set according to the policy exercise, set as the labeling. Further, standard sampling procedures, such as Latin-Hypercube, random and quasi-random sampling, fail to consistently provide an exploration advantage over each other in the case of complex systems and Agent-Based Model parameter-space exploration (Lee et al., 2015; Bergstra and Bengio, 2012). This is especially the case in high-dimensional spaces, where standard design of experiments are computationally expensive to compute and show little to no advantage over quasi-random sampling in practice (Bergstra and Bengio, 2012). Accordingly, we leverage both active learning[5] and semi-supervised learning[6] to sequentially sample the parameter space. In particular, unlabeled data is exploited through semi-supervised learning to assist the surrogate in actively selecting which unlabeled points to evaluate in each of multiple rounds.

As illustrative examples, we apply our procedure to two well known ABMs: the asset pricing model proposed in Brock and Hommes (1998) and the growth model developed in Fagiolo and Dosi (2003). Despite their relative simplicity, the two models might exhibit multiple equilibria, allow different behavioural attitudes (fundamentalist, trend follower, trend contrarian, rational in the case of the Brock and Hommes model and innovation vs. imitation prone behaviour in the Island model) and account for a wide range of dynamics, which crucially depends on (not so few) parameters.

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[3] In their example, the model is characterized by a single parameter.

[4] Also commonly referred to as an emulator, meta-model or model of a model.

[5] For a comprehensive survey of active learning algorithms, see Settles (2010).

[6] For a review of semi-supervised learning, see e.g. Zhu (2005); Goldberg et al. (2011).

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