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Chapter 12

Applications in human and social sciences

Over the last few years, there has been an explosion in the availability of continuous and spatially linked datasets, both formal (for example, economic time series) and informal (for example, crowd-sourced, geolocated twitter feeds). Social science is now in a position to better constrain model errors using dynamic DA. Indeed, this is essential if socioeconomic modeling is to fulfill its considerable potential. However, social scientists have largely restricted their research to static modeling traditions.

In this chapter, we will present some of the pioneering work in this vast domain. The first application is economics and finance, where there is obviously both a lot of dynamic data available and strong motivations to improve analysis and predictions. The second domain is that of traffic control, a subject with deep consequences for energy efficiency, pollution, global warming, and public health and safety. Finally, urban planning and management is an excellent use-case for exploiting the availability of linked geospatial and socioeconomic data.

12.1 ▪ Economics and finance

12.1.1 ▪ Presentation of the domain

One of the major challenges in finance today is the estimation of the volatility, σ. Adjoint methods can be, and are being, used to find the volatility for given stock prices. In macroeconomics, there is wider use of particle filter and sequential Monte Carlo methods for simulation and estimation of parameters.

12.1.2 ▪ Examples of DA problems in this context

12.1.2.1 ▪ Volatility estimation and option pricing

The evolution of stock market prices can be reasonably well described by Brownian motion [Oksendal, 2003] models of the form

$$\mathrm{d}S/S = \sigma\,\mathrm{d}W + \mu\,\mathrm{d}t,$$

which is an SDE, where $S(t)$ is the stock price, σ is the volatility, $\mathrm{d}W$ is the increment of a standard Brownian motion, μ is related to the interest rate, and t is time. Under suitable assumptions, and applying Itô calculus, this model can be transformed into a

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PDE of parabolic type, known as the Black–Scholes equation [Wikipedia, 2016b], for the option price, $V(S,t)$. The equation is

$$\frac{\partial V}{\partial t}+\frac{1}{2}\sigma^2 S^2\frac{\partial^2 V}{\partial S^2}=rV-rS\frac{\partial V}{\partial S},$$

where r is the return, or interest rate. We can thus consider the volatility as a quantification of the uncertainty of the future price of an asset. But the volatility is in general unknown and needs to be estimated so that the observed market prices are well reproduced by the equation. This in an inverse problem for σ given the observations of $V(S,t)$. Adjoint methods provide a very efficient way of solving this problem and can produce estimates of the so-called Greeks that are the sensitivities (or gradient components) of V with respect to S, t, r, and σ.

In the comprehensive monograph of Achdou and Pironneau [2005], numerical algorithms and methods are described for adjoint-based solution of the inverse problem for finding the volatility of different options. Recently, these and other methods, in particular particle filters, have been applied to the domain of high-frequency trading [Platania and Rogers, 2004; Duembgen and Rogers, 2014].

12.1.2.2 ▪ DA in economics

In Yong and Wu [2013], a number of examples in macroeconomics and international finance are studied with linear state space models, where parameter estimation plays a central role. In economics, Pitt and Shephard [1999] and Kim et al. [1998] have pioneered the application of particle filters in financial econometrics. More recently, Fernandez-Villaverde and Rubio-Ramirez [2007] have shown how particle filtering facilitates likelihood-based inference in dynamic macroeconomic models.

12.2 ▪ Traffic control

12.2.1 ▪ Presentation of the domain

The objective of traffic control is to improve the performance of a traffic system or to mitigate, as far as possible, the negative side effects of traffic. It strongly relies on our ability to monitor and forecast current and future traffic flow.

12.2.2 ▪ Examples of DA problems in this context

Key ingredients of traffic monitoring and forecasting are a relevant traffic flow model and a large enough observation set, with reasonable accuracy and good estimates on error statistics. State-of-the-art traffic flow models are written as a nonlinear conservation law for the vehicle density; see, e.g., the model by Work et al. [2010], based on the Lighthill–Whitham–Richards PDE. In this model, the flux function depends on the velocity of the vehicles, which in turn depends empirically on the vehicle density. Regarding observations, two kinds are considered in the literature: fixed sensors, e.g., on a given sensitive area of a highway, and GPS-enabled mobile devices.

12.2.2.1 ▪ Real-time monitoring and forecasting using stationary sensors

This experiment was conducted in Grenoble by Canudas De Wit et al. [2015]. They equipped Grenoble south ring (highly subject to morning and evening congestion) with stationary sensors at regular intervals, which measured data such as vehicle flow,

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mean velocity or individual vehicle velocity, and occupancy. The Grenoble Traffic Lab platform then produces real-time traffic monitoring and forecasting, which has been shown by the authors to be promising. They strongly rely on DA methods. First, they use a least-squares type method to calibrate the fluid dynamics model parameters (using the data). Then, they use a KF approach to provide traffic forecasts, using the data and calibrated model.

12.2.2.2 ▪ Highway traffic estimation using GPS mobile devices

Another source of data for traffic comes from GPS-equipped mobile devices (smartphones). As the penetration rate of such devices is ever increasing, it is relevant to use the data for traffic estimation. Of course the implied privacy issues are quite sensitive and should be considered while designing a system. The Mobile Century experiment by a Berkeley team, Herrera et al. [2010], circumvented the privacy issue by asking a team of students (with Nokia phones) to patrol the highway on designated itineraries. Without engorging the roads, they attained a 2% to 5% penetration rate and proved their system to be efficient; see Work et al. [2010]. This experiment used an EnKF described by Work et al. [2008], thanks to data collected on given lines on the highway. They used other data to perform cross-validation and showed a good agreement between the model and the observations.

12.3 ▪ Urban planning

12.3.1 ▪ Presentation of the domain

Town and urban areas are ever changing: old buildings razed to the ground, new buildings built, parks or green areas created, neighborhoods restructured, roads and transportation system changed, and so on. This continuous evolution affects both the environment and the human population: access to green areas, air quality, local climate, hydrology, ecology, extreme events such as floods, and more generally people's quality of life. Urban planning, from a DA point of view, aims to provide tools to urban managers and policy makers to monitor, forecast, and plan for a safe environment and preserve or improve quality of life. Typical questions that can be answered using land-use evolution modeling and DA are as follows: What variation on the urban environment will ensue from a given societal change? Which decision should be made to improve population access to green areas? What is the impact of an isolated decision on future urban hydrology?

12.3.2 ▪ Examples of DA problems in this context

12.3.2.1 ▪ Particle filtering for uncertainty reduction in land-use modeling

As can be observed in many application domains, the need for DA methods arises when modeling has reached a certain maturity and simple methods of model calibrating have reached their limit. Urban planning is no exception, and DA has recently been introduced to improve land-use change models and in particular to take into account uncertainties.

A Belgian initiative is interested in urban planning modeling using remote-sensing data. In the MAMUD project, Van de Voorde et al. [2013] designed and calibrated a land-use model using satellite data to assess the impact of city growth on the urban and suburban hydrology. DA methods were required when it became obvious that the uncertainties in the model as well as the data were proving to be a bottleneck for forecast accuracy. In the follow-up ASIMUD project, van der Kwast et al. [2011] proposed a particle filter algorithm to calibrate model parameters, while taking into account both model and data uncertainty and providing improved confidence intervals on the forecasts.

Another example of particle filtering for land-use change modeling is found in Verstegen et al. [2016]. In this study, the authors wondered whether systemic change could be detected using DA. In a case study of sugar cane expansion in Brazil, the particle filter combined with satellite data highlighted that the model structure and parameterization were nonstationary. They realized that a complex societal change was not captured by the stationary model. Their particle filter allowed systemic change in the model and notably improved the projections' confidence intervals.

12.3.2.2 ▪ Calibration of land-use and transportation integrated models

Land-use and transportation integrated (LUTI) models consider the coupling of land-use models and models of transportation of goods and people. Because of the coupling, they are more realistic for the assessment of the impact of urban planning policies; however, they are also more complex, and their calibration is a difficult task. In the project CITiES, DA is used for such a calibration. Capelle et al. [2015] first proposed calibrating a LUTI model using variational-type assimilation: they formulated the calibration as parameter estimation through the Levenberg–Marquardt optimization of a cost function. Gilquin et al. [2016] then proceeded further by introducing sensitivity analysis into the calibration procedure: in a first step, global stochastic sensitivity analysis ascertains to which parameters the model is the most sensitive; in a second step, optimization is done on these important parameters using the data. Compared to the classically used trial-and-error calibration procedures for LUTI models, these two studies showed a significant improvement on both the calibration quality and the computing time.

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