Causal Effects Under Spatial Confounding and Interference

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Abstract

Spatial causal inference is an emerging field of research with wide ranging areas of applications. As a key methodological challenge, spatial confounding and spatial interference can compromise the performance of standard statistical inference methods. In the current literature, there is a lack of appreciation of the connections between spatial confounding and interference. This could potentially lead to overspecialized silos of research. Therefore, we need further research to bridge such gaps theoretically, and to find creative solutions for complex spatial causal inference problems. This short paper offers a brief demonstration: It discusses the connections between spatial confounding and interference. An illustrative simulation study shows how commonly used approaches compare across four test scenarios. The simulation study is discussed with an emphasis on the promising performance of counterfactual prediction based inference methods.

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1 Introduction

Knowledge of cause and effect plays an important role in explaining past events and planning for future ones. Causal inference is, broadly speaking, the empirical quest for such knowledge. The last seventy years have witnessed the formation of statistical inference frameworks that revolutionised empirical approaches to causal inquiries. Most notably, we have the Potential Outcomes (PO) framework [9] which approaches the inference of causal effect via an analogy to randomised experiments. It would also be fitting to describe this progress as part of a wider intellectual movement propelled by mutually reinforcing forces such as the vogue of evidence-based policy, the availability of data, and the maturity of causal theories.

Spatial causal inference is causal inference in the presence of substantive spatial causal mechanisms. Here, space can be interpreted as either geographical or relational. Over recent years, spatial causal inference has emerged as an independent area of research. On the one hand this is motivated by empirical topics that are irreducibly spatial. For example, policing and neighborhood crimes, vaccination and disease spread, air pollution and health... This makes spatial causal inference a valuable methodological endeavour with real world impact. On the other hand, this is also characterised by unique analytical challenges associated with spatial causal mechanisms that cannot be simply conceptualised as standard randomised experiments.

This short paper aims to offer a synthesis of two key concepts in spatial causal inference with illustrative examples. The paper was motivated by my observation that, in the current literature, there is a lack of appreciation of the connections between key analytical concepts, which could potentially lead to overspecialised silos of methodological research. Despite recent efforts to document progress in spatial causal inference (e.g. [8]), we have more of an

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assemble of techniques rather than a cohesive picture of the field. I believe the field will benefit from a consolidation of existing understandings of spatial causal problems as well as approaches to meeting the analytical challenges. In this short paper specifically, the focus will be placed on spatial confounding and interference. In the rest of the paper, I will first reflect on the two concepts. Then, with a simulation study, I will compare commonly used approaches across settings of spatial confounding and/or interference. The simulation will be discussed with an emphasis on the promising performance of counterfactual prediction based causal inference methods as an example of creative approaches that are able to engage multiple methodological topics.

2 Challenges in spatial causal inference

Spatial causal inference is characterised by its unique methodological challenges. Individual units are embedded in spatial contexts, and they interact in a spatially structured way. This tends to create more complex dependence structures than standard non-spatial causal inference methods admit. The resulted statistical problems are commonly captioned as spatial confounding, spatial interference, and spatial heterogeneity. Here, let's focus on spatial confounding and spatial interference. Specifically, I want to draw attention to the connections between spatial confounding and interference. Besides conceptual connections, the two problems often coexist in real world scenarios. Therefore, although methodological developments typically target one or the other, it is important that we understand how spatial causal inference methods engage with and perform under both spatial confounding and interference.

2.1 Spatial confounding

Confounding is a classic causal inference problem. Confounders influence both the treatment allocation and the outcome, and therefore not adjusting for the confounder admits a spurious correlation between the treatment and outcome variables. In spatial causal inference, we are particularly interested in confounders with significant spatial patterns (e.g. Figure 1.a), a condition which makes confounding adjustment amenable to spatial statistical techniques. The best way to think of spatial confounding is as a shorthand for spurious correlation due to omission of spatial variables. In recent literature, spatial confounding is mainly covered by the area of research on causal effects under unmeasured confounding. Under unmeasured confounding, the causal parameter in a PO model (typically the Average Treatment Effect, ATE) cannot be fully identified. Progress has been made on identification with propensity score matching (e.g. [2] [7]), using confounder proxy variables (e.g. [3]). For causal effect estimation, there are techniques to derive bounds for the causal parameter, for example, through sensitivity analysis (e.g. [1]), nonparametric bounding and interval estimates (e.g. [5]).

2.2 Spatial interference

In causal inference, 'interference' refers to the existence of dependence of an observational unit's outcome on the treatments of other units. In the PO framework, no interference is one of the basic assumptions, commonly known as one component of the Stable Unit Treatment Value Assumption. Spatial interference refers to scenarios of causal interference resulted from spatial interaction among the units. A typical case is treatment spillover, where a unit is exposed to a direct treatment as well as an indirect spillover treatment from its neighbours (e.g. Figure 1.b). This is what makes the interference problem unique, as we may

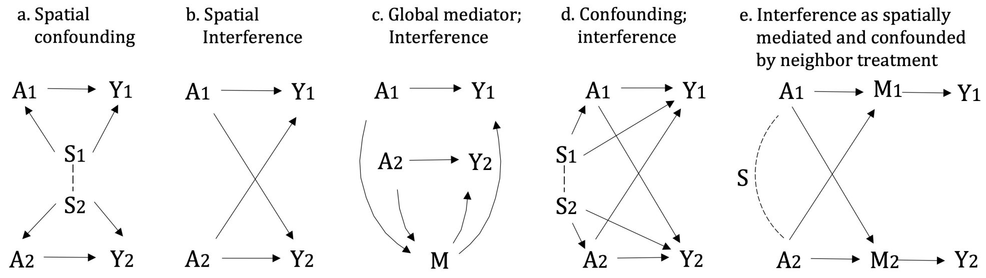

Figure 1 Illustrative Directed Acyclic Graphs (DAG) for spatial confounding and interference. (Subscript denotes location.)

be interested in more than one causal estimands. The identifiability of causal effects under interference has been thoroughly investigated, among others, by Manski [6], and Forastiere [4]. Short of fieldwork-based exposure mapping to obtain true exposure levels, the estimation relies on strong restriction assumptions about the structure of causal interaction. Apart from interaction restrictions, the identification also relies on assumptions of no unmeasured confounding.

2.3 Common sources and shared solutions?

One way to appreciate how confounding and interference are connected is to reflect on the relationship between causal mechanisms and their reduced statistical representations. Although spatial confounding and spatial interference are conceptually distinct, they could be manifestations from the same underlying causal mechanism. In other words, it is possible that a given spatial causal mechanism, when translated as a statistical model, can present with either confounding or interference or both. As an illustrative case: When measuring the effect of vaccination on disease spreading, it can be conceptualised as an interference case (where the unvaccinated population receives a spillover protection from the vaccinated via mediation of group immunity, Figure 1.c); or it can be conceptualised as a confounding case (where the neighbourhood context of individuals confounds their actually received levels of protection as well as health outcome, Figure 1.a). Spatial confounding and interference can also coexist (e.g. Figure 1.d). With the example of neighbourhood crime rate interventions: The interference aspect is that intervention on one neighbourhood could affect crime rates of adjacent ones. There could coexist an element of confounding if intervention and crime rate variables are spatially distributed and a shared spatial trend creates a spurious dependence between them.

We can also try to understand the connection between spatial interference and confounding through the language of statistical causal inference. In a way, we can say that, a spatial interference problem is a spatial mediation problem wrapped within a confounding problem (e.g. Figure 1.e). After we peel away the confounding part with, for example, propensity score methods, the task of estimating direct and indirect effects is in spirit a task of estimating path specific causal effects. In the style of mediation analysis, the effect of direct treatment can be estimated conditional on indirect treatment levels and vice versa (e.g. [10]; [11]) . In other words, an indirect effect is a causal effect mediated by the spatial interaction structure of the observational units, while the existence of such a structure usually also implies some degree of spatial confounding.

If spatial interference and confounding are so closely linked, what does this mean for methodology developments? To approach this question, first we have to better understand how the performance of existing methods generalises over spatial confounding and interference problems. So far, we have limited knowledge on this issue, as confounding and interference have been handled in separate strands of literature. To gain some insights, an illustrative simulation study is carried out.

3 Simulation study

The simulation study covers test scenarios of spatial confounding, spatial interference, and the coexistence of the two. Tested methods include two popular approaches to spatial causal inference: propensity score based adjustments, and spatial regression. Also tested is causal effect estimation based on counterfactual prediction of unobserved potential outcomes (also known as imputation based method). The counterfactual prediction approach is relatively new and has shown potential in addressing complex spatial causal inference problems.

3.1 Experiment design

The experiment is based on a basic setup. For the basic setup, the test dataset is generated in the following way: We have n observational units characterised by k covariates X^z drawn from a uniform distribution. Each unit inhabits a random location on a square. Its neighbours are defined as the set of units within a certain distance band. Its neighbourhood attributes X^g are represented by the average values of its neighbours' covariates. The assignment of direct treatment is independently determined by a unit's attributes X^z . The treatment Z is drawn from a Bernoulli distribution based on treatment propensity $e^z(X^z)$. A unit's outcome is determined only by its direct treatment status, $Z = 1$ treated and $Z = 0$ not treated. Accordingly, each unit has two potential outcomes, one of which is observed. The potential outcomes corresponding to direct treatment Z are $Y^z = Z * \tau^z + X^z * \beta + \epsilon, \epsilon^{i.i.d.} \sim\ N(0,1)$, where τ^z is the average treatment effect parameter of interest. To reflect spatial causal inference problems, different spatial causal mechanisms are added to the basic setting. This includes the following test scenarios:

(a) Spatial interference: In this scenario, besides direct treatment, a unit's outcome is also affected by its exposure to a neighbourhood treatment spillover G , $G = 1$ receiving spillover and $G = 0$ no spillover. The neighbourhood exposure G is determined by a unit's neighborhood covariate levels based on propensity $e^g(X^g)$. The marginal potential outcome corresponding to neighbourhood exposure G is $Y^g = \tau^g * G$, where τ^g is the average indirect treatment effect parameter. A unit's observed outcome is $Y = Y^z + Y^g$. Accordingly, each unit has four potential outcomes, one of which is observed.

(b) Spatial confounding: To introduce spatial confounding, the X^z covariates are spatially smoothed, which introduces a common spatial pattern in the treatment and outcome variables.

(c) Interference and confounding: A test scenario where both interference and confounding from scenarios (a) and (b) are present.

(d) Non-linearity: On top of scenario (c), a non-linear function is used to generate the outcome variable.

The following list of causal inference methods are tested. They are denoted as:

- IMP: Imputing unobserved potential outcomes with non-parametric models, followed by inverse probability weighting to estimate average causal effects.

- NS: A baseline non-spatial PO model.
- NSP: Non-spatial PO model with propensity score adjustment.
- S: A baseline spatial model. The model takes the form of a spatial regression, as spatial econometric models are common in the estimation of spillover effects. The model is formulated as a PO model with spatially lagged treatment and confounder variables.
- SP: Model S with propensity score adjustment.

Some further clarifications: In the simulation, all the methods are implemented in their basic form for a fair comparison. While misspecification of the interference structure and inaccuracy of propensity score estimation are important sources of bias, in this experiment the test is kept simple. Where needed, true propensity scores and true interference network is used. For each scenario, the tests are run with sample size 1000, covariate dimension 5.

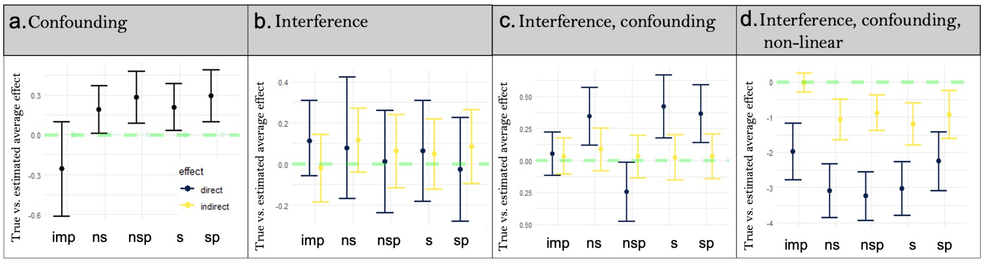

Figure 2 Main results of simulation experiments.

3.2 Test results

Test results are reported in Figure 2. The four subplots corresponds to the four test scenarios. For each test scenario, the estimated average treatment effects from the five models are benchmarked on ground truth. A few findings from the results:

(1) Across all test scenarios, comparing the performance of models 'NS' with 'S', and models 'NSP' with 'SP', we can see that the incorporation of spatial regression adjustment does not necessarily help to improve estimation accuracy. More generally, in applied cases it is difficult to verify the specification of spatial regression models, which can be a significant problem for causal inference tasks.

(2) Comparing the performance of models 'NS' with 'NSP', and models 'S' with 'SP', the incorporation of propensity scores helps to adjust the estimates in the correction direction for most test scenarios. This is including the scenario with spatial interference and no confounding (Figure 2.b).

(3) Comparing Figure 2.c with other scenarios, we can see that the coexistence of interference and confounding is challenging, as most models perform worse under this scenario. Meanwhile, compared with other models, the estimation accuracy of the counterfactual prediction based method 'IMP' does not deteriorate significantly when spatial confounding and interference coexist, suggesting a robustness of this approach.

(4) Across all test scenarios, comparing the performance of 'IMP' models with others, we can see that the counterfactual prediction based method performs as well as the other methods in recovering the true causal effect. While propensity score based adjustments and spatial regression techniques are mainstream and have enjoyed decades of refinement, the counterfactual prediction approach is relatively new to spatial causal inference. Recently, the approach has been employed by Davis et al. [2] in a spatial confounding setting, and by Forastiere et al. [4] in a network interference setting. I believe the counterfactual prediction approach is a promising direction of further methodological research. It is flexible enough to accommodate complex cases of spatial causal inference. And, it provides alternative ways to derive uncertainty quantification for models and parameters.

4 Conclusions

Spatial causal inference is an emerging field of research with wide ranging areas of applications. It is one of the methodological frontiers in the ongoing causal modelling movement. Complementary to existing review papers, this short piece offers a synthesis of two important concepts in spatial causal inference: spatial confounding, and spatial interference. A key message here is that: In the current literature, there is a lack of appreciation of the connections between core analytical concepts. This could potentially lead to overspecialised silos of research. Respectively, I believe several directions of research could benefit the field: Theoretically, we need further efforts on consolidating existing understandings of spatial causal problems and approaches to meeting the analytical challenges. Methodologically, counterfactual prediction is a promising direction of research which could potentially lead to flexible methods for complex spatial causal inference cases.

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