STATE-OF-THE-ART REPORT

Double Machine Learning for Spatio-Temporal Conflict Data

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January 21, 2026

1 Introduction

The availability of high-dimensional, fine-grained spatio-temporal data through remote sensing [1–3] and the emergence of new conflict event databases [4] have transformed conflict research in recent years [5]. Additionally, advancements in machine learning (ML) have led to substantial success in forecasting the timing, location, and fatalities of conflict [6–8]. For policymakers and humanitarian organizations seeking to prevent conflict, allocate aid, or guide post-conflict recovery, simply anticipating where and when conflict will occur is insufficient; they also need to understand the underlying causal relations [9, 10]. This necessitates moving from pure forecasting to causal inference, enabling the determination of the causal impact of specific interventions (e.g., foreign aid allocation [9, 11, 12] or military actions [13, 14]) and external shocks (e.g., economic shocks [15]).

While existing ML models can forecast conflict with increasing accuracy, they are inherently limited in their ability to explain underlying causes [16, 17]. Progressing from prediction to explanation remains a key challenge [18, 19]. The high dimensionality of conflict data typically arises from the use of fine-grained spatial grid cells with monthly observations [6, 7, 20]. For instance, Racek, Thurner, and Kauermann [6] employed 10,640 grid cells ($0.5° \times 0.5°$ lattice) covering Africa with monthly data from 2000 to 2020. As a result, traditional parametric approaches often fail in these settings due to the large number of potential confounders and the curse of dimensionality [21]. While standard nonparametric ML methods (e.g., Random Forests, Gradient Boosting) can effectively navigate this complexity to optimize predictive performance, they fail to provide valid causal inference due to the inherent introduction of regularization bias [22, 23]. Double Machine Learning (DML) offers a solution to these fundamental limitations by orthogonalizing the estimation problem and separating the prediction of nuisance functions from the estimation of causal parameters [22]. Consequently, one can retain the flexibility of modern ML methods to adequately adjust for observed confounding variables while obtaining unbiased estimates of treatment effects, making the framework highly suited for causal inference tasks with high-dimensional data [24, 25].

However, the diffusion of conflict through spatial (spillover) and temporal (carryover) dimensions complicates the application of causal inference [13, 14]. For instance, violence in one location increases the likelihood of subsequent violence in adjacent areas, while past conflict often predicts future conflict in the same location [6]. These dynamics violate the Stable Unit Treatment Value Assumption (SUTVA), as a treatment applied to one unit may affect outcomes in neighboring units and in future time periods [13, 26]. The standard assumption that observations are independent and identically distributed (i.i.d.) is also fundamentally violated by conflict data [27, 28]. Furthermore, unobserved spatially correlated confounders and temporal dependence structures can bias treatment effect estimates and invalidate standard inference procedures [29–31]. To ensure accurate estimation, causal frameworks must be adapted to explicitly model and account for these challenges.

This report reviews the methodological foundations and the current state of the art for applying Causal Machine Learning (CML), specifically DML, to spatio-temporal data in the context of conflict research. Section 2 covers current conflict forecasting literature and motivates the shift towards causal inference. Section 3 discusses the challenges and solutions regarding spatial and temporal data, followed by an outline of the theoretical foundations of DML and its extensions in section 4.

2 From Forecasting to Causal Inference

2.1 The State of the Art in Conflict Forecasting

Contemporary conflict forecasting has moved beyond small-scale country-specific designs used in earlier research [17, 32]. Through efforts such as the Violence and Impacts Early-Warning System (VIEWS) [33] or the ACLED Volatility Risk Index/CAST [34], combined with a "revolution" in data and methodology, the scope and predictive performance of forecasting in conflict research have increased substantially [5]. Current data—led by datasets such as the Uppsala Conflict Data Program's Georeferenced Event Dataset (UCDP GED) [35] and the Armed Conflict Event and Location Dataset (ACLED) [36]—captures local dynamics through global collections of individual armed conflict events on a daily basis over long time series. This highly disaggregated microdata, containing millions of data points, is then often leveraged to perform a spatio-temporal aggregation; typically, a PRIO-GRID lattice [37] with $0.5° \times 0.5°$ spatial grid cells (55×55 km^2 at the equator) and a monthly temporal resolution is used [7, 33]. These event-based frameworks are usually complemented with structural covariates—static, long-term data like economic and social indicators—to combine conflict dynamics with underlying socio-economic conditions [33, 34, 37]. Moreover, the integration of remote sensing data variables (e.g., vegetation indices, satellite imagery) has further enhanced this spatial granularity [1–3].

Recent models perform well at static risk assessment but have limited capabilities in predicting conflict dynamics (e.g., onsets, escalations, and terminations) [3, 38]. Methodologically, most of today's approaches use nonparametric ensembles (e.g., XGBoost or Random Forests) that excel at capturing nonlinear interactions and minimizing predictive error (e.g., Brier scores) [33, 39]. A current evolution in the field is the shift from manual feature engineering to deep learning, with some frontier models adopting architectures that autonomously learn representations and capture intricate long-term temporal dependencies [5]. Examples include Long Short-Term Memory (LSTM) networks, Recurrent Neural Networks (RNNs), and Transformers, such as Temporal Fusion Transformers (TFTs) [7, 38]. Another emerging approach is direct forecasting from news corpora using Transformer-based Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) [40, 41]. While such "black box" ML models maximize metrics like AUROC, they lack interpretability and obscure structural mechanisms [17, 19]. Most empirical studies also treat conflict diffusion simply as a nuisance, controlling for it by including simple spatial and temporal lags; this leads to very limited insights into the diffusion of armed conflict [6]. Research by Racek, Thurner, and Kauermann [6] addresses these gaps by using a Generalized Additive Model (GAM) with nonparametric smoothing. This allows the model to capture the spatio-temporal diffusion of conflict over large distances and temporal lags of up to 24 months while remaining fully interpretable.

2.2 The Missing Causal Understanding

The majority of current research in the field is focused on forecasting, with models designed to maximize predictive accuracy over interpretability, leaving the understanding of conflict's root causes and treatment evaluation underexplored [17, 19]. Yet, as Cederman and Weidmann [17, p. 23] argue, "theory-free prediction does little to guide intervention without knowledge about the drivers of conflict". Since prediction and explanation represent distinct epistemological goals, a model that excels at forecasting with high accuracy may reveal nothing about underlying mechanisms and relationships [16]. Therefore, architecture selection often involves a trade-off between model accuracy and explanatory capabilities [42]. Even if the predictive accuracy of a model is high—for instance, successfully forecasting increasing levels of violence—policymakers may lack the trust to take action and authorize costly interventions [10, 43]. Furthermore, even fully interpretable models like GAMs cannot differentiate between causation and correlation; as Cederman and Weidmann [17] note, forecasting models identify correlates of conflict, not causes. Crucially, policy decisions require counterfactual reasoning, which purely observational forecasting models cannot provide [18]. Relying on associations without considering confounding or reverse causality can therefore lead to misguided policies and interventions (e.g., erroneous foreign aid allocation, ineffective military actions) [11, 13]. CML bridges this gap by enabling valid statistical inference for treatment effects while utilizing high-dimensional data [18, 23].

2.3 Causal Machine Learning

Causal effect estimation is challenging because of the inability to observe both treated and untreated potential outcomes for the same unit simultaneously; this is generally referred to as the fundamental problem of causal inference [44]. CML addresses this by combining the flexible estimation power of ML with principles from causal inference [23, 45]. While traditional econometric approaches struggle with high-dimensional covariate spaces [21] and standard ML methods introduce regularization bias [18, 25], CML builds on the potential outcomes framework [46] to formalize causal inference through counterfactual reasoning and relax restrictive parametric assumptions of traditional regressions [23, 47]. This means explicitly modeling the confounding structure by flexibly approximating nuisance functions and adjusting for high-dimensional confounding [18]. The framework therefore allows for valid effect estimation in environments with a high number of covariates [21] and complex nonlinear relations [47].

A multitude of methodological approaches for effect estimation in CML have emerged, with recent research moving beyond the global Average Treatment Effect (ATE) and predominantly focusing on Heterogeneous Treatment Effect (HTE) via the Conditional Average Treatment Effect (CATE) [48, 49]. The following taxonomy gives a broad overview of the major areas[1]: **Tree-based methods**, most notably Causal Forests, are specialized and adapted versions of the Random Forest algorithm that split to maximize treatment effect heterogeneity across leaves, as opposed to prediction accuracy [50, 51]. **Meta-learners** decompose the problem into multiple standard prediction subproblems that can then be solved with any common supervised learning method [48]. For instance, the T-learner (T for Two) fits separate base-learners for treatment and control units, and subsequently calculates the difference between their estimates; other variants include the S-learner or the X-learner [24, 45, 48]. Double Machine Learning represents a general framework within

[1]Note that these categories are not mutually exclusive and represent conceptually distinct concepts. For instance, DML can be seen as a statistical principle (bias-correction) that is implemented within specific algorithms (e.g., Causal Forests, R-learner, DR-learner), while meta-learners can be seen as architectural wrappers (model composition).

the larger group of **orthogonalization methods** that utilizes Neyman-orthogonal score functions to control for regularization bias in high-dimensional settings (for an extensive discussion, see section 4) [22]. Furthermore, extensions to Instrumental Variables (IV) and Difference-in-Differences (DiD) have recently emerged to address situations where the unconfoundedness assumption is violated [22, 52, 53].

Within conflict research, CML has received limited application. Notable exceptions include: Christiansen et al. [54], who applied spatio-temporal models to analyze the relationship between armed conflict and forest loss in Colombia; Kuzmanovic et al. [9], who developed a CML framework for predicting HTEs of aid disbursements; and studies evaluating the impact of US airstrikes on insurgent violence in Iraq [13, 14]. Additional applications include [20, 55, 56]. However, addressing the challenges of spatio-temporal diffusion when applying the DML framework remains an open research area.

3 Spatio-Temporal Causal Inference

Standard causal inference assumptions for independent cross-sectional observations often fail in the context of complex dependencies across space and time. Therefore, when attempting to infer conflict relations and dynamics using real-world data, a multitude of problems arise. The following section outlines the principal challenges and current state-of-the-art solutions: Interference/Persistence (section 3.1), Confounding (section 3.2), Positivity (section 3.3), and Statistical Dependence (section 3.4). Conflict data also presents specific challenges related to data quality—such as reporting bias—which will not be discussed in detail here (for further reading, see [57–59]).

3.1 The Stable Unit Treatment Value Assumption

The validity of causal estimation relies on the Stable Unit Treatment Value Assumption (SUTVA) [60]. SUTVA requires that there is no interference. Formally, the potential outcome Y_{it} of unit i at time t depends only on the specific treatment D_{it} assigned to that unit at that time: $Y_{it} = Y_{it}(D_{it})$. This assumption is violated by two mechanisms: **Spatial Spillover** occurs when the outcome for unit i depends on the treatment vector of its spatial neighbors $\mathbf{D}_{\mathcal{N},t}$: $Y_{it} = Y_{it}(D_{it}, \mathbf{D}_{\mathcal{N},t})$ [61, 62]. **Temporal Carryover**, on the other hand, arises when the treatment applied at time t continues to influence outcomes at $t + k$, violating the assumption of instantaneous effects [63, 64]. Therefore, an outcome Y_{it} depends on the whole treatment history $\tilde{D}_{it}$: $Y_{it} = Y_{it}(\tilde{D}_{it})$ with $\tilde{D}_{it} = \{D_{it}, D_{i,t-1}, \ldots, D_{i,0}\}$.

Since conflict is a dynamic system in the real world, interventions in one region potentially lead to diffusion effects over space and through time; for instance, violence may displace activity to neighboring areas over time [13]. There are several approaches to address these violations: **Geometry-Based** methods use concentric rings or spatial buffers to define mappings that capture a unit's exposure (or non-exposure) and estimate the effect of nearby treatments on outcomes [26, 65]. **Stochastic Interventions/Point Processes** model treatments as probability distributions across space and time by redefining estimands to explicitly incorporate interference patterns [13, 14, 55]. **Network/Dependency Graphs** are often used for non-geographic interference (e.g., supply chains) and relax

SUTVA by allowing interference only between connected nodes [66, 67]. Finally, **Non-parametric Smoothing** assumes interference follows a continuous diffusive function that is modeled using decay basis functions or neural networks [6, 68].

3.2 Spatial & Dynamic Confounding

Even if interference is modeled correctly, causal identification also relies on the assumption of Unconfoundedness. This requires that the potential outcomes are independent of treatment assignment D_{it} conditional on observed covariates X_{it}: $Y_{it}(d) \perp D_{it} \mid X_{it}$. In spatio-temporal settings, unobserved heterogeneity in both dimensions frequently violates this assumption: **Spatial Confounding** takes place when unobserved variables U_i (e.g., terrain, governance, culture) influence both treatment assignment and outcome while exhibiting spatial correlation [29]. So if researching conflict $D_{it} \leftarrow U_i \rightarrow Y_{it}$ and U_i is spatially clustered (most conflict drivers are not randomly distributed [54, 69]), standard estimators (that assume i.i.d. errors) will produce biased estimates by attributing the effect of geography to the treatment [69, 70]. **Dynamic Confounding** (also called time-varying confounding) materializes in the temporal dimension, especially through feedback loops where past outcomes influence future treatments ($Y_{i,t-1} \rightarrow D_{it}$) [18, 64]; for instance, increased conflict intensity of a previous timeframe's outcome ($Y_{i,t-1}$) may influence new interventions (D_{it}), which then affects future conflict outcomes ($Y_{i,t+1}$). Such a structure violates the strict exogeneity assumption because the covariates required to adjust for the confounding (the history) are themselves affected by prior treatments [64]. Consequently, identification in this context requires the strongest assumption of Sequential Ignorability [71]: treatment assignment must be independent of past potential outcomes conditional on the full history of observables [64, 72, 73].

Mitigation strategies in recent literature include: **Sequential Peeling**, a method to address feedback loops where effects are estimated recursively to isolate the causal effect of the current treatment from future confounders (for more details, see section 4.2) [67, 72]. Another dynamic deconfounding method is to use history-dependent propensity scores to "break" the feedback loop [13, 14]. **Spatial Basis Functions & Smoothing** model spatial confounding as a smooth surface by using flexible functions—for instance, non-parametric smoothing or tensor splines—to absorb trends that would otherwise lead to biased treatment effects [6, 69]. **Data Transformations** can be used in the case of static spatial confounding (fixed factors that do not change over the study period). Examples include DiD extensions [74–77] and within-group (WG)/first-differencing (FD) transformations [78]. There are also methods that utilize **Latent Modeling** and **Proxy Learning** in situations where confounders are unobserved. These techniques use high-dimensional data (or auxiliary variables) to learn a low-dimensional latent representation of the confounders, for instance with an autoencoder [68] or even multimodal [79, 80]. See also [25, 26, 54, 73].

3.3 Positivity

Another causal identification requirement is the Positivity (also sometimes called Overlap) assumption, which requires that treatment assignment is not deterministic given the covariates [81]. This implies that every unit must have a non-zero probability of receiving the treatment; formally, the propensity scores must be strictly bounded away from zero and one: $0 < \epsilon < P(D_{it} = 1 \mid X_{it}) < 1 - \epsilon \quad \forall X_{it} \in \mathcal{X}$. For continuous treatments, positivity requires sufficient variation in the treatment intensity conditional on controls [22, 82]. In conflict research, this is often violated by structural zeros or ones (e.g., some regions may have a near-zero probability of conflict no matter the covariates), caused by strategic targeting that leaves no comparable counterfactual units (a structural violation) [9]. In high-dimensional settings and when treatments are continuous, this can lead to issues since the overlap deteriorates asymptotically; as the dimension of X_{it} increases, units become unique and propensity scores collapse to the boundaries (a practical violation) [82–84]. These violations result in the inverse probability weights exploding, inflating variance and introducing bias. Solutions include **Trimming** the sample based on the propensity score to discard extreme observations and restrict inference to subsamples with enough overlap [85]; **Overlap Weights** to continuously down-weight units in the tails of the propensity score distribution [86]; and **Shift Interventions** that estimate the effect of small perturbations to the treatment [82, 87]. The first two are best suited for binary treatments, whereas Shift Interventions are designed for continuous treatments.

3.4 Statistical Dependence

Besides the above-mentioned general identification assumptions for causal inference, there are also estimation/inference assumptions. Conflict data violates the i.i.d. assumption since it exhibits strong autocorrelation [6, 27, 28]—spatio-temporal dependencies where error terms are correlated across units. This leads to two distinct issues: (1) Inference failure, where standard variance estimators underestimate uncertainty and standard errors are too small, resulting in Type I errors and spurious significance [69, 88]. (2) Data leakage when utilizing random cross-validation splits and when training units are spatio-temporally close to test units. This is particularly relevant for DML, since the framework relies on the regularity condition of i.i.d. observations and uses cross-fitting to obtain valid standard errors and convergence rates (see section 4 for further details) [22, 89]. Recent research addresses this issue via **Block Cross-Fitting**, which splits data by time periods or spatial clusters rather than randomly and per unit to preserve the dependence structure within folds [78]. **Neighbors-Left-Out Cross-Fitting** builds on this by excluding neighboring observations, thereby preventing information leakage from spatially or temporally adjacent units (see section 4.3 for more details) [73]. The method is specifically designed for time-series and spatially dependent data where dependence decays over time and distance. Another related approach is **Multiway Cross-Fitting**, which accounts for correlation along multiple dimensions simultaneously (e.g., clustering by both time period and spatial unit in panel data) [89]. Additionally, inference should use **HAC Estimators** (Heteroskedasticity and Autocorrelation Consistent) to address issue (1) and correctly quantify uncertainty in the presence of spatial and temporal correlation [88–91].

4 Double Machine Learning

4.1 The Basics

The high-dimensional setting of conflict data, where the number of potential confounders is large relative to the number of observations, necessitates the use of ML methods. While standard ML methods achieve strong predictive performance through regularization, the latter also introduces systematic bias in treatment effect estimates that does not vanish with increasing sample size. Double Machine Learning (DML)—formally introduced by Chernozhukov et al. [22] in 2018—resolves the regularization bias problem and allows for valid causal inference combined with flexible ML methods.

To illustrate the concept of DML, consider the following Partially Linear Regression (PLR) model [92]:

$$\begin{aligned} Y &= D\theta_0 + g_0(X) + U, \quad & \mathbb{E}[U|X,D] = 0 \\ D &= m_0(X) + V, & \mathbb{E}[V|X] = 0 \end{aligned}$$

where Y denotes the outcome (e.g., conflict fatalities), D the treatment (e.g., military intervention, aid allocation), U and V disturbances, and $X \in \mathbb{R}^p$ a high-dimensional vector of confounders (e.g., GDP, population density, conflict event data). θ_0 is the causal parameter of interest that captures the causal effect of D on Y, while the nuisance functions $g_0(X)$ and $m_0(X) = \mathbb{E}[D|X]$ (the propensity score) are unknown and potentially complex. The challenge lies in obtaining a valid estimate of θ_0 despite the high dimensionality of the nuisance functions $\eta_0 = (g_0, m_0)$.

Simply using a flexible ML algorithm like a Random Forest to estimate θ_0 by (1) estimating g_0 and (2) regressing the residuals $Y - \hat{g}(X)$ on D leads to biased results. Modern ML methods rely on regularization to manage high-dimensional data, which introduces regularization bias; the estimation error $\hat{g}(X) - g_0(X)$ remains correlated with D through their mutual dependence on X. This bias propagates directly into $\hat{\theta}$, does not vanish at rate $1/\sqrt{n}$, and invalidates standard inference.

DML resolves this by employing Neyman orthogonality and constructing an orthogonal score that is insensitive to first-order errors in nuisance estimation. In addition to partialling out X from Y, DML also residualizes the treatment. This isolates the variation in D and Y that is not explained by X by estimating the nuisance functions $\hat{g}(X)$ and $\hat{m}(X)$ to create residuals $\tilde{Y} = Y - \hat{g}(X)$ and $\tilde{D} = D - \hat{m}(X)$. Formally, this estimator depends on a score function $\psi(W;\theta,\eta)$ that is insensitive to small perturbations in the nuisance parameters η. In the PLR example, the orthogonal score function takes the form:

$$\psi(W;\theta,\eta) = (Y - g(X) - D\theta)(D - m(X))$$

where $W = (Y, D, X)$ and $\eta = (m, g)$. This satisfies the Neyman orthogonality condition:

$$\partial_\eta \mathbb{E}[\psi(W;\theta_0,\eta_0)][\eta - \eta_0] = 0$$

This condition ensures that first-order errors in estimating $\hat{g}$ and $\hat{m}$ vanish, leaving only second-order errors that do not affect the asymptotic distribution of $\hat{\theta}$.

To prevent overfitting, DML utilizes cross-fitting: (1) the sample is randomly partitioned into K folds; (2) the nuisance functions are estimated on the remaining $K - 1$ folds; (3) the orthogonal score is evaluated on the held-out fold; (4) the results are either averaged across folds (DML1) or pooled into a single estimating equation solved over all observations (DML2). Under regularity conditions, this separation guarantees that the final DML estimator is $\sqrt{n}$-consistent and asymptotically normal:

$$\sqrt{n}(\hat{\theta} - \theta_0) \xrightarrow{d} \mathcal{N}(0, \sigma^2)$$

provided that the nuisance estimators converge at a rate of $n^{-1/4}$ or faster.

4.2 DML for Dynamic Treatment Effects

The standard DML framework as described in section 4.1 addresses regularization bias in static settings. However, applying it to spatio-temporal conflict data introduces new challenges—which were discussed in section 3—that require specialized extensions. Lewis and Syrgkanis [72] (see also [93]) were among the first researchers to introduce a solution for DML with Dynamic Treatment Effects (DTE), which focuses on dealing with temporal persistence and feedback loops (see section 3.2); their proposed Dynamic DML estimation extends the Neyman orthogonality principle to dynamic treatment schemes (settings where multiple treatments are assigned over time and can have a causal effect on future outcomes or the state of the treated unit).

A partially linear state space Markov decision process $\{X_t, D_t, Y_t\}_{t=1}^{m}$ (for a time horizon $t = 1, \dots, m$) where $X_t \in \mathbb{R}^p$ denotes the high-dimensional state, $D_t \in \mathbb{R}^d$ the treatment, and Y_t the outcome (at time t respectively) will serve as a simplified application example of the algorithm, similar to the PLR used in section 4.1. The structural equations take the form:

$$
\begin{aligned}
X_t &= A \cdot D_{t-1} + B \cdot X_{t-1} + W_t \\
D_t &= m(D_{t-1}, X_t) + V_t \\
Y_t &= \theta_0' D_t + \mu' X_t + U_t
\end{aligned}
$$

where W_t, V_t, U_t are disturbances, A captures how treatments affect future states, B governs how past states affect the next periods state, and θ_0 is the contemporaneous treatment effect. Further, μ is the contemporaneous effect of the states on the outcome and m is the treatment assignment function (propensity). The goal is to estimate the effect of a change in the treatment policy on the final outcome Y_m. Therefore, the sequence of dynamic treatment effects θ_t for $t \in \{1, \dots, m-1\}$ with $\theta_t = \mu' B^{t-1} A$ (θ_t represents the causal effect of a treatment impulse at time $m-t$ on the outcome at time m) can be used to capture effects operating through state changes. To estimate the expected difference between applying and not applying the treatment, it suffices to estimate the full sequence of dynamic treatment effects $\theta_0, \dots, \theta_m$.

To address the estimation problem, Dynamic DML builds on the principles from section 4.1 by constructing Neyman orthogonal moments at each stage via double residualization. The key innovation is a sequential peeling strategy that estimates effects backwards from the final period m to the first period; the algorithm proceeds for $t = 0, 1, \dots, m$—and assuming access to a dataset with n i.i.d. samples from the Markovian process—as follows:

1. **Nuisance Estimation:** For the current lag t, estimate the conditional expectations of the outcome and all relevant treatments with respect to the current history X_{m-t}. Recalculating the treatment residuals is necessary because treatment residuals from previous steps were calculated conditional on future states. Fit the nuisance model for the outcome $\hat{g}_t(x) = \mathbb{E}[Y_m \mid X_{m-t} = x]$ and for each $j \in \{0, \dots, t\}$ the treatment model $\hat{m}_{j,t}(x) = \mathbb{E}[D_{m-j} \mid X_{m-t} = x]$ using cross-fitting. Finally, compute the corresponding residuals $\tilde{Y}_{m,m-t}$ and $\tilde{D}_{m-j,m-t}$.

2. **Peeling:** Subtract the causal contribution of all subsequent treatments using previously estimated effects $\hat{\theta}_0, \dots, \hat{\theta}_{t-1}$ to isolate the variation in the outcome residuals

that is attributable to the treatment at $m-t$. Thus, the "calibrated" outcome residual $\bar{Y}_{m,t}$ is calculated by subtracting the weighted future treatment residuals:

$$\bar{Y}_{m,t} = \tilde{Y}_{m,m-t} - \sum_{j=0}^{t-1} \hat{\theta}_j' \tilde{D}_{m-j,m-t}$$

3. **Orthogonal Estimation:** Estimate θ_t by solving the Neyman orthogonal moment condition:
$$\frac{1}{n}\sum_{i=1}^{n}(\bar{Y}^i_{m,t} - \theta_t \tilde{D}^i_{m-t,m-t})\tilde{D}^i_{m-t,m-t} = 0$$

Furthermore, the framework generalizes beyond the Markovian case utilized thus far to Structural Nested Mean Models (SNMMs) [63] with minimal modifications. In this setting, restrictive independence assumptions are replaced by the weaker condition of sequential conditional exogeneity; this essentially requires that treatments are randomized conditional on past history. SNMMs also allow for arbitrary state spaces and discrete or continuous treatments, employing blip functions for identification. These functions capture the expected difference in the outcome if the treatment is removed, while continuing with a target policy thereafter. Nevertheless, applying the framework to empirical settings like conflict research remains challenging due to multiple factors. For instance, even after easing the assumption to sequential conditional exogeneity, conflict settings might still violate it since unobserved strategic factors that drive both treatment and outcome (spatial confounding) are often present. The model also does not take spatial spillovers into account, thereby violating SUTVA, which is essential for valid causal inference.

4.3 DML for Heterogeneous Treatment Effects in Dynamic Panels

The frameworks presented in section 4.1 and section 4.2 estimate the ATE[2]. For policy applications or to analyze conflict diffusion, understanding how treatment effects vary across contexts and characteristics is important. While the dynamic DML framework (section 4.2) addresses temporal feedback loops, conflict data presents additional challenges (see section 3). Semenova et al. [73] (also [95]) present an inference approach that tackles both of these aspects. Their method estimates the CATE—which captures treatment effect heterogeneity as a function of unit characteristics—and works with high-dimensional panels; they specifically address static spatial confounding (unobserved unit-specific heterogeneity/unit fixed effects) and statistical dependence (weak dependence).

Consider the following adjustment to the PLR model from section 4.1 that allows for heterogeneous effects ($i = 1, \ldots, N$ denotes units, and $t = 1, \ldots, T$ time):

$$\begin{aligned} Y_{it} &= D_{it}'\theta_0 + e_0(X_{it}) + \xi_i^E + U_{it}, \quad && \mathbb{E}[U_{it}|D_{it}, X_{it}, \Phi_{it}] = 0 \\ D_{it} &= m_{i0}(X_{it}) + V_{it}, && \mathbb{E}[V_{it}|X_{it}, \Phi_{it}] = 0 \end{aligned}$$

where θ_0 is the treatment effect parameter vector characterizing the CATE, Φ_{it} is the filtration of predetermined variables for unit i prior to period t, D_{it} is the technical treatment vector (defined as the interaction between the base treatment P_{it}—the vector with policy

[2]For both, HTE estimation exists. See [94] for the DML CATE extension and the original DML for DTE paper [72].

variables—and the dictionary of transformations $K(X_{it})$: $D_{it} := P_{it} \cdot K(X_{it}))$, $e_0(X_{it})$ is the complex confounding function of time-varying controls, and ξ_i^E is the unobserved outcome unit fixed effect (fixed spatial confounding). The error term U_{it} is assumed to satisfy sequential conditional exogeneity.

Standard fixed effects estimation is problematic in high-dimensional dynamic settings since it often leads to biased results and overfitting. The authors therefore take a fixed effects approach in which they approximate the vector of unobserved components of unit effects ξ^E by a weakly sparse vector. Instead of treating the effects as a nuisance to be differenced out, the method estimates them using Lasso. This assumes that the unit-specific deviations are well-approximated by a sparse vector, allowing them to be learned consistently alongside other nuisance parameters even when the number of units is large.

For the estimation of the high-dimensional parameter θ_0, the DML principle of orthogonalization is applied to partial out the influence of confounders and unit effects. The unit-specific nuisance functions are defined as:

$$m_{0i}(X_{it}) = \mathbb{E}[D_{it}|X_{it}, \Phi_{it}] = d_0(X_{it}; \xi_i),$$
$$g_{i0}(X_{it}) = \mathbb{E}[Y_{it}|X_{it}, \Phi_{it}] = m_{i0}(X_{it})'\theta_0 + e_0(X_{it}) + \xi_i^E$$

with ξ denoting a fixed vector of unit-specific fixed treatment selection effects. The residuals $V_{it} := D_{it} - d_{i0}(X_{it})$ and $\tilde{Y}_{it} := Y_{it} - g_{i0}(X_{it})$ then result in the orthogonalized equation:

$$\tilde{Y}_{it} = V_{it}'\theta_0 + U_{it}, \quad \mathbb{E}[U_{it}|V_{it}, X_{it}, \Phi_{it}] = 0,$$

which identifies θ_0 as the coefficient of the best linear projection of $\tilde{Y}_{it}$ on V_{it}.

As already mentioned in section 3.4, regular cross-fitting does not work for the assumed data structure. Semenova et al. [73] resolve this with Neighbors-Left-Out (NLO) cross-fitting, where the time series is partitioned into K adjacent blocks $\{M_k\}_{k=1}^K$. Then temporal neighbors are excluded by defining a new quasi-complement for each block as $M_k^{qc} = \{M_1, \ldots, M_K\} \setminus \{M_l : l \in \mathcal{N}(k)\}$, where $\mathcal{N}(k)$ denotes k and its immediate neighbors. Consequently, the method ensures approximate independence between training and test samples.

The complete algorithm consists of three steps:

1. **Nuisance Estimation:** Estimate the nuisance functions $\hat{g}$ and $\hat{m}$ using appropriate modeling structures and ML methods that can handle fixed effects (for instance, Lasso for the sparse fixed effects) as well as NLO cross-fitting. Afterwards, calculate the residuals $\widehat{\tilde{Y}}_{it}$ and $\widehat{V}_{it}$.

2. **Orthogonal Estimation:** Estimate the causal effect parameter vector (the CATE function) $\hat{\theta}_0$ by regressing $\widehat{\tilde{Y}}_{it}$ on $\widehat{V}_{it}$ using Lasso:

$$\hat{\theta} = \arg\min_{\theta \in \mathbb{R}^d} \frac{1}{NT} \sum_{i,t} \left(\widehat{\tilde{Y}}_{it} - \widehat{V}_{it}'\theta \right)^2 + \lambda_\theta \|\theta\|_1,$$

where $\lambda_\theta = C_\theta \sqrt{\log d / NT}$ and C_θ is a penalty parameter. This selects the relevant interaction terms that drive treatment heterogeneity.

3. **Debiased Inference:** To correct for the regularization bias introduced in step 2, construct valid Gaussian confidence intervals for CATE using debiased Lasso with an approximate inverse of the residual covariance matrix.

Similar to the dynamic DML framework in section 4.2, applying this approach to conflict data comes with potential challenges. For instance, the weak sparsity assumption on residual unit effects ξ^E may be violated by real-world data when every spatial unit has dense unit-specific confounders. While the model addresses temporal autocorrelation, it assumes cross-sectional independence between units. The framework also does not explicitly address spatial spillovers, a key concern for conflict research (section 3.1).

4.4 Other Literature

Other recent literature has further expanded DML for dynamic and panel data settings. In environments where unobserved time-invariant unit-specific confounding is the primary concern, Clarke and Polselli [78] extend DML to static panels with fixed effects. They demonstrate an adaptation of the Neyman orthogonal score to remove unobserved heterogeneity while allowing for complex nuisance functions. Bodory, Huber, and Laffers [96] introduce a weighting-based DML extension strategy for estimating dynamic treatment effects that robustly adjusts for time-varying confounding across treatment sequences. Another recent paper that is directly relevant for the context of conflict diffusion develops DML estimators for impulse response functions in local projections, which model how treatment effects propagate over multiple time periods [97].

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