Peering Inside the Black Box: Exploring Innovations in Interpretable Machine Learning and Causal Inference for the Explanation of Political Violence

PhD Project

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Abstract

The use of machine learning (ML) within social science research is increasingly common. Yet, a gap remains in how we use these models in inference settings to explain, rather than predict or classify, phenomena. Concurrently, there is a growing need in policymaking to make sense of increasingly common, but complex, machine learning strategies. Despite ML models being able to capture the complexity of social phenomena to a greater extent than traditional statistical models, they have been considered less useful for explanations and inferences, in part due to being viewed as 'black box' methods that are substantively opaque. Recent methodological advances show that we can make sense of these complex ML models and use them for both explanation and causal inferences. These advances are grouped under the subfields of 'Interpretable machine learning' (IML) and 'Causal machine learning' (Causal ML). To date, these innovations have not been sufficiently translated within the social sciences. This research aims to fill this gap and demonstrate the utility of using ML methods not just for prediction, but for explanation and inference also. I will do so by engaging in translation, innovation, and finally application of these methods to the study of political violence. Studying the application of ML methods in political violence is particularly important as understanding the determinants of conflict allow proactive interventions and policy solutions in various forms. Political violence is, however, complex, and multi-causal, and therefore conventional parametric methods are unlikely to model these dynamics effectively. For policymaking relevance, it is imperative that we can explain why a conflict event might occur as well as if and when. Methodologically, I aim to demonstrate how researchers can use ML to capture and explain complex social phenomena, and in the process open avenues for greater policymaking relevance and impact. A broad research question that could apply to this PhD project, then, is "How can we leverage developments in complex machine learning strategies for explanation and inference in social science contexts?" Substantively, I aim to use these tools to advance our understanding of the mechanisms of political violence.

1 Introduction

The use of machine learning (ML) within social science research is increasingly common. Yet, a gap remains in how we use these models in inference settings to explain, rather than predict or classify, phenomena. Concurrently, there is a growing need in policymaking to make sense of increasingly common, but complex, machine learning strategies.

Machine learning methods can give us greater fidelity over prediction problems, due in part to treating the data generating process as learnable.[1] This has the benefit of removing researcher degrees of freedom in parameter selection and lending itself to analysis in high-dimensional space.[2] In addition, ML methods optimise for prediction by introducing intended bias through regularisation to minimise variance.[3] ML optimises the bias/variance trade-off to minimise generalisability error in prediction whereas OLS focuses on variance reduction.[4] These benefits result in greater prediction accuracy relative to their statistical counterparts.[5]

Despite ML models being able to capture the complexity of social phenomena to a greater extent than traditional statistical models, they have been considered less useful for explanations and inferences.[6] One reason is that they are viewed as 'black box' methods and are considered substantively opaque.[7] Parameters in various ML models cannot be easily interpreted substantively.[8] Another drawback of using ML for explanation and inference is the introduction of bias to estimators, leading to potentially biased coefficients.[9] ML predictions risk failing to

[1] Kleinberg, J., et al. "Prediction Policy Problems," *American Economic Review,* 105(5), 491-495, 2015.
[2] Athey, S., Imbens, G. "Machine Learning Methods That Economists Should Know About," *Annual Review of Economics,* 11, 685-725, 2019.
[3] Ibid.
[4] Ibid.
[5] Kleinberg, J., et al. 2015.
[6] Athey, S. "Machine Learning and Causal Inference for Policy Evaluation," *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining,* 5-6, 2015. ; Grimmer, J. "We Are All Social Scientists Now: How Big Data, Machine Learning, and Causal Inference Work Together," *PS: Political Science and Politics,* 48(1), 80-83, 2014. ; Rudin, C. "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead," *Nature Machine Intelligence,* 1, 206-215, 2019.
[7] Bathaee, Y. "The Artificial Intelligence Black Box and the Failure of Intent and Causation," *Harvard Journal of Law & Technology,* 31(2), 890-939, 2018. ; Moraffah, R., et al. "Causal Interpretability for Machine Learning - Problems, Methods and Evaluation," *SIGKDD Explorations Newsletter,* 22(1), 18-33, 2020. ; Sullivan, E. "Understanding from Machine Learning Models," *The British Journal for the Philosophy of Science,* 73(1), 2022.
[8] Molnar, C. "Interpretable Machine Learning: A Guide for Making Black Box Models Explainable," Munich, Christoph Molnar, 2022.
[9] Kleinberg, J., et al. 2015.

capture the complex relationships through underfitting or, conversely, losing generalisability to other data by overfitting.[10]

Studying the application of ML methods in political violence is particularly important as understanding the determinants of conflict allow proactive interventions and policy solutions in various forms. Political violence is, however, complex, and multi-causal, and therefore conventional parametric methods are unlikely to model these dynamics effectively. Existing scholarship such as the ViEWS competition, which saw a range of novel modelling approaches, has attempted to use ML to predict.[11] However, this has failed to evidently inform policymaking regarding the appropriate action in cases of realised or potential political violence.[12] For policymaking relevance, it is imperative that we can explain *why* a conflict event might occur as well as *if* and *when*.

Recent methodological advances in computing and statistics show, however, that we *can* make sense of these complex ML models and use them for both explanation and causal inference.[13] These advances are grouped under the subfields of 'Interpretable machine learning' (IML) and 'Causal machine learning' (Causal ML). To date, these innovations have not been sufficiently translated within the social sciences. This research aims to fill this gap and demonstrate the utility of using ML methods not just for prediction, but for explanation and inference also. I

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[10] Mullainathan, S., Spiess, J. "Machine Learning: An Applied Econometrics Approach," *The Journal of Economic Perspectives,* 31(2), 87-106, 2017.

[11] Hegre, H. et al., "ViEWS: A political violence early-warning system," *Journal of Peace Research,* 56(2), 155-174, 2019.

[12] Bätz, K., Klöckner, A., Schneider, G. "Challenging the Status Quo: Predicting Violence with Sparse Decision-Making Data," *International Interactions,* 2022. ; Bowlsby, D., Chenoweth, E., Hendrix, C., Moyer, J. "The Future is a Moving Target: Predicting Political Instability," *British Journal of Political Science,* 50(4), 1405-1417, 2020. ; Brandt, P., D'Orazio, V., Khan, L., Li, Y., Osorio, J., Sianan, M. "Conflict Forecasting with Event Data and Spatio-Temporal Graph Convolutional Networks," *International Interactions,* 2022. ; Colaresi, M., Mahmood, Z. "Do the robot: Lessons from machine learning to improve conflict forecasting," *Journal of Peace Research,* 54(2), 193-214, 2017. ; D'Orazio, V., Lin, Y. "Forecasting conflict in Africa with automated machine learning systems," *International Interactions,* 2022. ; Ettensperger, F. "Forecasting conflict using a diverse machine-learning ensemble: Ensemble averaging with multiple tree-based algorithms and variance promoting data configurations," *International Interactions,* 2021. ; Mueller, H., Rauh, C. "Using Past Violence and Current News to Predict Changes in Violence," *International Interactions,* 2022. ; Radford, B., "High Resolution Conflict Forecasting with Spatial Convolutions and Long Short-Term Memory," *International Interactions,* 2022. ; Randahl, D., Vegelius, J. "Predicting Escalating and De-Escalating Violence in Africa Using Markov Models," *International Interactions,* 2022.

[13] Molnar, C. 2022. ; Ribeiro, M., Singh, S., Guestrin, C. ""Why Should I Trust You?" Explaining the Predictions of Any Classifier," arXiv, 1-10, 2016. ; Shapley, L. "A Value for n-Person Games," in H. Kuhn and A. Tucker (eds.) *Contributions to the Theory of Games II,* Princeton, Princeton University Press, 307-317.

will do so by engaging in *translation, innovation,* and finally *application* of these methods to the study of political violence.

My PhD project will translate, innovate, and apply cutting-edge methods in the emerging fields of IML and Causal ML.[14] Methodologically, I aim to demonstrate how researchers can use ML to capture and explain complex social phenomena, and in the process open avenues for greater policymaking relevance and impact. A broad research question that could apply to this PhD project, then, is *"How can we leverage developments in complex machine learning strategies for explanation and inference in social science contexts?"* Substantively, I aim to use these tools to advance our understanding of the mechanisms of political violence.

My thesis will seek to answer the following research question:

1. *"How can interpretable ML methods help us better understand the determinants of civil war onset?"*
2. *"How can ML be used to improve modelling contexts with procedural elements in the social sciences?"*
3. *'How can causal ML be used to generate causal inferences with plausibly exogenous randomised thresholds in the social sciences?'*

[14] Athey, S., Imbens, G. 2019. ; Athey, S., Imbens, G. "Recursive partitioning for heterogeneous causal effects," *PNAS,* 113(27), 7353-7360, 2016. ; Wager, S., Athey, S. "Estimation and Inference of Heterogenous Treatment Effects using Random Forests," *Journal of the American Statistical Association,* 118(523), 1228-1242, 2018.

2 Literature Review

2.1 Political Violence

The ability of ML to predict in complex high-dimensional environments can be illustrated in the context of political violence. Political violence is complex due to large variability in factors that affect whether a political violence event occurs, making it the ideal area of study for the translation of IML and Causal ML methods. Theorised causal factors include the type of actor, geospatial variability, neighbouring activities, and political and cultural context, to name a few. They also operate at different structural levels, from sub-national to transnational.

2.2 Statistical Modelling of Political Violence

Initial attempts to understand political violence events such as civil wars were made by researchers such as Collier & Hoeffler and Hegre & Sambanis. They used logistic regression, focusing on concepts like ethnic heterogeneity and natural resources.[15] Statistical modelling requires several assumptions, with resulting limitations. The key limitations of this approach are that important explanatory variables may be omitted, relationships between outcome and explanatory variables are presupposed during model selection and thus different relationship shapes may be overlooked, and the use of country-year explanatory variables led to biases in modelling that predicted the continuation of peace in countries that have been peaceful for some time, and vice versa for those with recent conflicts.[16] These limitations lead to poor predictive power, raising questions about the capacity of these models to capture the complexity of conflict processes. This weakens the inferential claims derived from these models regarding the causes of conflict.

2.3 ML Modelling of Political Violence

In response to this, conflict theorists have adopted ML strategies to better capture the complexity of the processes and interactions leading to political violence. The last decade has

[15] Collier, P., Hoeffler, A. "Greed and grievance in civil war." Oxford Economic Papers, 56(4), 563–595, 2004. ; Fearon, J. D., Laitin, D. "Ethnicity, insurgency, and civil war." *American Political Science Review,* 97(01), 75–90, 2003 ; Hegre, H., Sambanis, N. "Sensitivity analysis of empirical results on civil war onset." *Journal of Conflict Resolution,* 50(4), 508–535, 2006.

[16] Mueller, H., Rauh, C. "Reading Between the Lines: Prediction of Political Violence Using Newspaper Text," *American Political Science Review,* 112(2), 358-375, 2018.

been dominated by algorithmic models trained on within-country data.[17] Tools and databases such as confliBERT, ACLED & CAMEO have led to a significant increase in predictive power, which is indicative of better capturing the complexity of political violence.[18] Table 1 summarises how scholars have applied ML to the study of political violence. However, adopters of ML have failed to use these methods to *explain* political violence due to the supposed 'black box' nature of the algorithms in question.[19] I intend to fill this gap with the following methods.

Methods	*Data*	*Key Literature*	*Task*	*Prediction level*
Neural Networks	Events; Geospatial	Bang et al., 2017; Brandt et al., 2022; Radford, 2022.	Prediction	Country-year; PRIO-GRID cell-month;
Random Forest	Fixed effects	Muchlinski et al., 2015.	Prediction & Explanation	Country-year
autoML	Events	D'Orazio & Lin, 2022.	Prediction	PRIO-GRID cell-month
Ensembles	Events; Fixed effects	Ettensperger, 2021; Hegre et al., 2019; Olabanjo et al., 2021.	Prediction	PRIO-GRID cell-month
Topic Modelling	Newspaper text	Mueller & Rauh, 2018; Mueller & Rauh, 2022.	Prediction	Country-month; Sub-national;
Markov Model	Fixed effects	Randahl & Vegelius, 2022.	Prediction	PRIO-GRID cell-month
Generative Model	Events; Fixed effects	Verma et al., 2018.	Prediction	Country-year

Table 1: ML Modelling of Political Violence

[17] Bätz, K., Klöckner, A., Schneider, G. 2022. ; Bowlsby, D., Chenoweth, E., Hendrix, C., Moyer, J. 2020. ; Brandt, P., D'Orazio, V., Khan, L., Li, Y., Osorio, J., Sianan, M. 2022. ; Colaresi, M., Mahmood, Z. 2017. ; D'Orazio, V., Lin, Y. 2022. ; Ettensperger, F. 2021. ; Muchlinski, D., Siroky, D, et al. "Comparing Random Forest with Logistic Regression for Predicting Class-Imbalanced Civil War Onset Data." Political Analysis, 24, 87-103, 2015. ; Radford, B., 2022. ; Randahl, D., Vegelius, J. 2022.
[18] Hu et al., "ConfliBERT: A Pre-trained Language Model for Political Conflict and Violence," *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies,* 5469-5482, 2022. ; Mueller, H., Rauh, C. 2022. ; Raleigh, C., Linke, A., Hegre, H., Karlsen, J. "Introducing ACLED: An Armed Conflict Location and Event Dataset," *Journal of Peace Research,* 47(5), 651-660, 2010.

[19] Cederman, L., Weidmann, N. "Predicting armed conflict: Time to adjust our expectations?" Science, 355, 474-476, 2017.

2.4 IML & Causal ML

Interpretable machine learning concerns *explaining why* ML models made decisions.[20] IML methods can be categorised across 3 specifications – intrinsic vs. post hoc, by the result of the method, and whether the method is model-specific or agnostic.[21] Models that are intrinsically interpretable have simple structures that facilitate analysis. In contrast, IML can be applied to complex ML models post-training in order to explain predictions and decisions.[22] The output of IML varies from summary statistics to visualisations and analysing model internals. Finally, some IML methods are specific to certain models, such as in the case of neural networks. In contrast, model-agnostic methods have interpretable applicability to all ML models.[23] I will seek to combine model-specific and model-agnostic IML methods for maximum applicability for future researchers to utilise my innovations.

Researchers have shown that it is possible to adapt ML strategies, affecting the bias/variance trade-off to account for intended bias. Thus, statistical inference is possible whilst leveraging the predictive fidelity of ML strategies, strengthening our trust in our inferences as ML better captures the true data generation process.[24] This is causal ML. For example, Wager & Athey developed the 'causal forest,' an adaptation of Breiman's random forest method.[25] This method ensures consistency with an asymptotic sampling distribution whilst maintaining a data-driven means of determining feature-value weighting, enabling it to predict, classify, and infer in

[20] Athey, S., Imbens, G. 2019. ; Athey, S., Imbens, G. 2016. ; Molnar, C. Wager, S., Athey, S. 2018.

[21] Molnar, C. 2022., Ch 3.2.

[22] Ibid. ; Ribeiro, M., Singh, S., Guestrin, C. 2016.

[23] Ibid. Ch 6. ; Ribeiro, M., Singh, S., Guestrin, C. "Model-agnostic interpretability of machine learning." *ICML Workshop on Human Interpretability in Machine Learning*, 2016.

[24] Arti, S., Hidayah, I., Kusumawardani, S. "Research Trend of Causal Machine Learning Method: A Literature Review," *International Journal on Informatics for Development,* 9(2), 111-118, 2020. ; Athey, S., Imbens, G. 2019. ; Athey, S., Imbens, G. 2016. ; Bacardi, A., Naghi, A. "The Value Added of Machine Learning to Causal Inference: Evidence from Revisited Studies," *Tinbergen Institute Discussion Paper, No. TI 2021-001/V,* Tinbergen Institute, Amsterdam and Rotterdam, 2021, https://www.econstor.eu/bitstream/10419/229707/1/21001.pdf, (last access 11 November 2022). ; Chernozhukov, V., et al. "Double/Debiased/Neyman Machine Learning of Treatment Effects," *American Economic Review,* 107(5), 261-265, 2017. ; Wager, S., Athey, S. 2018. ; Kleinberg, J., et al. 2015. ; Sekhon, J. "The Neyman-Rubin Model of Causal Inference and Estimation via Matching Methods," in J. Box-Steffensmeier, H. Brady, D. Collier (eds.) *The Oxford Handbook of Political Methodology,* Oxford, Oxford University Press, 15-57, 2007.

[25] Breiman, L. "Random Forests," *Machine Learning,* 45, 5-32, 2001. ; Kleinberg, J., et al. 2015. ; Wager, S., Athey, S. 2018.

complex high-dimensional space with much covariate interactability.[26] The use of ML does not, however, remove the need for rigorous research design and assumption specification.[27]

[26] Ibid, 2.

[27] Sekhon, J. "Opiates for the Matches: Matching Methods for Causal Inference." *Annual Review of Political Science,* 12(1), 503, 2009.

3 Research Projects

I plan to engage in a three-paper PhD project. The following papers are connected methodologically as they seek to *translate*, *innovate,* and *apply* innovations in ML methods to demonstrate how ML can be used to explain and infer when studying complex social phenomena. Substantively, they all concern furthering our understanding of the mechanisms of political violence.

Paper 1

I intend to research how we can better understand the determinants of political violence using innovations in IML. The research question for this paper is: *"How can interpretable machine learning methods help us better understand the determinants of civil war onset?"*

Design

I will run a neural network model, due to its own model-specific IML capacities, and combine them with model-agnostic measurements.[28]

First, I will calculate and analyse Shapley Values, a model-agnostic method, to explain variation in outcome due to their ubiquitous use in data science, despite relative sparseness in the social sciences.[29] A limitation of this method is the high computational need.[30]

Next, I will calculate and analysis counterfactuals according to the method proposed by Dandl et al., in combination with a nondominated sorting genetic algorithm (NSGA-II) in order to identify the minimum variable change required to move from predicting peace to civil war onset in observations of interest.[31] This has broad policy implications as policymakers wish to know which countries are most at risk of civil war given small feature value changes.

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[28] Molnar, C. chapter 10, 2022.
[29] Molnar, C. chapter 9.5.4, 2022.
[30] Ibid.
[31] Dandl, S., et al. "Multi-Objective Counterfactual Explanations," *International Conference of Parallel Problem Solving from Nature – PPSN 2020,* 448-469, 2020. ; Deb, K., Pratap, A., Agarwal, S., Meyarivan, T. "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II," *IEEE Transactions of Evolutionary Computation,* 6(2), 182-197, 2002.

Finally, I will innovate concept detection using neural networks, a model-specific IML strategy, to test if these methods can be used to better understand which concepts are powerful explainers of civil war onset.[32] I will compare these analyses with prior papers mentioned above in section 2.2 and 2.3 to test IML's applicability to better understand complex social phenomena.

Data

Civil war is here defined as a conflict between state and non-state actors confined to the borders of a single nation that led to at least 25 battle-related deaths in a given year.[33] A preliminary set of feature values is detailed in Table 2 below. I will seek to expand this through an additional literature review this year.

Concept	***Level***	***Data Source***	***Key Research***
Regime Characteristics	National	Polity5	*Gelpi & Avdan, 2018; Gurses & Mason, 2010; Hegre, 2014; Vreeland, 2008;*
Refugee Camps	Sub-national	UNHCR & FICSS	*Zhou & Shaver, 2021;*
Deadly Electoral Violence	Sub-national	DECO	*Fjelde & Höglund, 2022 ;*
State Military Power	National	Global Firepower	*Hegre & Sambanis, 2006; Lankford, 2011; Phillips, 2015;*
Internet Penetration	National	Facebook Estimated Advertising data	*Fatehkia, Kashyap, Ingmar, 2018; Howard et al., 2011; Wolfsfeld, Segey, Sheafer, 2013;*

Table 2: Paper 1 Feature Variables

[32] Molnar, C. chapter 10.3, 2022.
[33] Gleditsch, N., Petter; P., Wallensteen, M., Sollenberg, M., Strand, H. "Armed Conflict 1946–2001: A New Dataset," *Journal of Peace Research*, 39(5), 2002.

Paper 2

This paper will study how ML optimisation can be used to overcome limitations in modelling contexts with a procedural element. My research question is *"How can ML innovations be used to improve modelling contexts with procedural elements in the social sciences ?"*

Design

I will study the impact of the co-evolution of non-state actor relationships and characteristics on the onset, extension, and termination of civil conflict. Prior work has been published on the impact of rebel interdependencies, but little has been done on the way in which characteristics and relationships co-evolve to affect conflict outcomes.[34]

I will employ an SAOM as they excel in the study of the co-evolution of characteristics and relationships.[35] A criticism of SAOMs is that results are said to be a product of a 'self-fulfilling prophecy' whereby the researcher observes results because it was modelled as such. In order to address this limitation, I propose to specify parameters with data-driven ML models, removing researchers' degrees of freedom by using empirical data to inform the parameter settings of these models. To help me apply these methods robustly, I plan to audit the MY461 'Social Network Analysis' course next year and pursue further training.

Data

A challenge of this paper will be availability of trustworthy actor relationship data due to the oft informal nature of interrelationships between non-state actors. If I find that my primary sources are lacking in comprehensiveness, I will enrich the data according to Akcinaroglu's prior data collection processes, which involves extracting data from Keesing World Events Archive and Google book excerpts. I already have the necessary documentation and code to do so.[36]

[34] Akcinaroglu, S. "Rebel Interdependencies and Civil War Outcomes," *The Journal of Conflict Resolution,* 56(5), 879-903, 2012. ; Bohle, H. "Geographies of Violence and Vulnerability an Actor-Oriented Analysis of the Civil War in Sri Lanka," *Erdkunde,* 61(2), 129-146, 2007.
[35] Snijders, T. "Stochastic actor-oriented models for network change," *Journal of Mathematical Sociology,* 21(1-2), 149-172, 1996.
[36] Akcinaroglu, S. 889-900, 2012.

Concept	*Level*	*Data Source*	*Key Research*
Actor Characteristics	Sub-national	UCDP; EPR; V-DEM; SIENA;	Akcinaroglu, 2012; *Bohle, 2007;*
Actor Relationships	Sub-national	EPR; Government Documents;	*Akcinaroglu, 2012;* *Clayton & Gleditsch, 2014;* *Park, 2018;*

Table 3: Paper 2 Feature Variables

Paper 3

This paper will argue for the applicability of research designs' such as that of Ferwerda & Miller for generating causal inference.[37] I will extend this by utilising ML methods that better approximate the true data generation process and utilise the large amounts of observational conflict data. I will combine this data with a justification of plausibly exogenous randomisation of demarcation. My research question is *'How can causal ML be used to generate causal inferences with plausibly exogenous randomised thresholds in the social sciences?'*

Design

Given the empirical and theoretical importance of borders for conflict, I want to exploit the British-French enforced 1916 Sykes-Picot borders in the Middle East to generate causal insights.[38] I intend to study the impact that differing colonial strategies has on ethnic conflict. Prior studies observed the effect of French and British colonial strategies on public good provision, but never conflict.[39]

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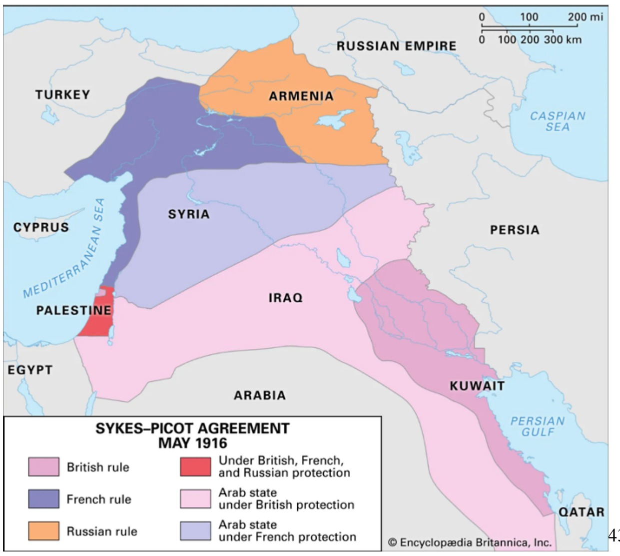
[37] Ferwerda, J., Miller, N. "Political Devolution and Resistance to Foreign Rule: A Natural Experiment," *American Political Science Review,* 108(3), 642-660, 2014.

[38] Downes, A. "More Borders, Less Conflict? Partition as a Solution to Ethnic Civil Wars," *The SAIS Review of International Affairs,"* 26(1), 49-61, 2006. ; Gurr, T. "Peoples Against States: Ethnopolitical Conflict and the Changing World System: 1994 Presidential Address," *International Studies Quarterly,* 38(3), 347-377, 1994.

[39] Lee, A., Schultz, K. "Comparing British and French Colonial Legacies: A Discontinuity Analysis of Cameroon," *Quarterly Journal of Political Science,* 7, 1-46, 2012. ; McDougall, J. "The British and French Empires in the Arab World: Some Problems of Colonial State-formation and its Legacy," in S Cummings & R Hinnebusch (eds.) *Sovereignty After Empire: Comparing the Middle East and Central Asia,* Edinburgh, Edinburgh University Press, 2011. ; Yakoubi, M. "The French, the British and their Middle Eastern Mandates (1918-1939): Two Political Strategies," *Revue Française de Civilisation Britannique,* XXVII-1, 1-18, 2022.

Research suggests the borders enforced were near arbitrary – leading to the formation of 'artificial states' by ignoring ethnic, linguistic and religious cleavages.[40] Sykes is quoted as saying "I should like to draw a line from the 'E' in Acre to the last 'K' in Kirkuk.[41]" Those near the border, such as in the case of the Iraq (British) and Syria (French) border, had different colonial rulers with differing occupation strategies, despite being from the same communities prior.[42]



[43]

Figure 1: *Sykes-Picot Border Map*

I will translate causal forests to execute my research.[44] This method was selected due to its non-linearity and ability to predict/classify in high-dimensional space whilst generating valid causal inferences.[45] A challenge will be ensuring comprehensive parameter selection in order to satisfy conditions for causal inference.

[40]Awan, A. "Architects of Failure: 100 years of Sykes-Picot," *History Today,* 16 May 2016, https://www.historytoday.com/archive/history-matters/architects-failure-100-years-sykes-picot , (last accessed 26 November 2016). ; Bâli, A. "Sykes-Picot and "Artifical" States," *AJIL Unbound,* 110, 115-119, 2016. ; Osman, T. "Why border lines drawn with a ruler in WW1 still rock the Midlde East," *BBC News,* 14 December 2013, https://www.bbc.co.uk/news/world-middle-east-25299553, (last accessed 26 November 2022).
[41] Wright, R. "How the Curse of Sykes-Picot Still Haunts the Middle East," *The New Yorker,* 30 April 2016, https://www.newyorker.com/news/news-desk/how-the-curse-of-sykes-picot-still-haunts-the-middle-east, (last accessed 26 November 2022).
[42] Ibid. ; Bâli, A. 2016.
[43] Encyclopædia Britannica. *"Sykes-Picot Agreement* [image]," https://www.britannica.com/event/Sykes-Picot-Agreement#/media/1/577523/205635, (last accessed 26 November 2022).
[44] Wager, S., Athey, S. 2018.
[45] Wager, S., Athey, S. 2018.

Data

I will operationalise proximity to borders using geo-referenced events data. Additional control variables will be added as I engage in this project.

Type	***Concept***	***Data Source***	***Key Research***
Dependant	Ethnic Conflict Events	UCDP; ACLED; EPR; EAC;	*Esteban, Mayoral & Ray, 2012; Fearon & Laitin, 2003; Sambanis, 2001;*
Feature	Regime Type	Polity5	*Sørli, Gleditsch & Strand, 2005;*
Feature	Ethnic Fractionalisation	HIEF	*Sørli, Gleditsch & Strand, 2005;*
Feature	Proximity to Border	GeoDataSource	*Downes, 2006; Gurr, 1994;*

Table 4: Paper 3 Feature Variables

Design Considerations

Across all three papers, advanced data manipulation will be necessary to prepare the data for analysis. In addition, the correlation between hand-coded datasets such as ACLED, and machine-coded data such as GDELT, has shown to be mediocre.[46] I will prioritise hand-coded data. I have reviewed the codebooks of these datasets and trust the collection process to a greater extent.

Since violence and civil conflicts are rare events, I will borrow methods from medical statistics to deal with the inherent class-imbalanced nature of these datasets. I will test an under-sampling technique – Tomek Links, and an over-sampling technique – SMOTE.[47]

[46] Hammond, J., Weidmann, N. "Using machine-coded event data for the micro-level study of political violence," *Research and Politics,* 1-8, 2014.

[47] Blagus, R., Lusa, L. "Class prediction for high-dimensional class-imbalanced data," *BMC Bioinformatics,* 11(523), 1-17, 2010. ; Lema, G., Nogueira, F., Aridas, C. "Imbalanced-learn: A Python Toolbox to Tackle the Curse of Imbalanced Datasets in Machine Learning," *Journal of Machine Learning Research,* 18(17), 1-5, 2017. ; Khalilia, M., Chakraborty, S., Popescu, M. "Predicting disease risks from highly imbalanced data using random forest," *BMC medical informatics and Decision Making,* 11(51), 1-13, 2011.

Ethical Considerations

My chief ethical concern here regards the potential impact of my results. I am wary of generating information that might be used against groups in conflict settings. I attempt to mitigate this concern through my large-n approach.

4 Conclusion

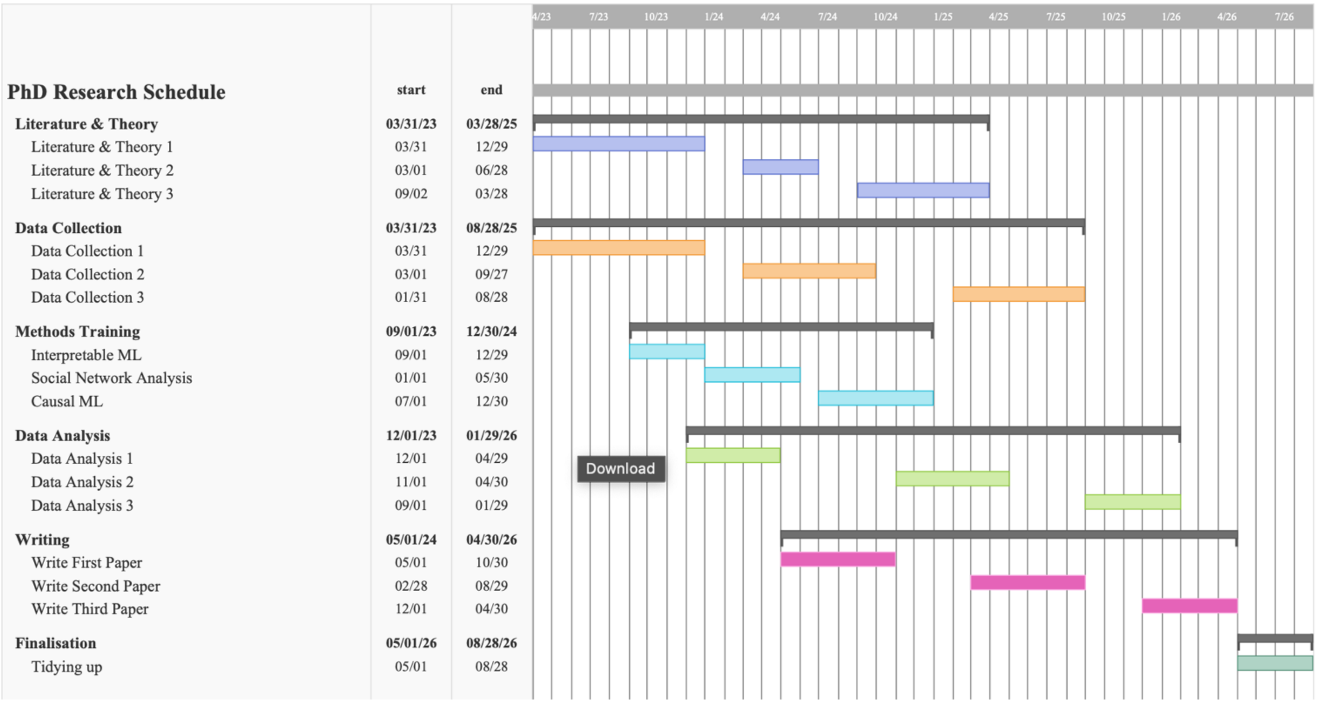


Figure 2: PhD Timeline

Figure 2 outlines my proposed research pipeline. I aim to complete this 3-paper PhD within 3 years, by the summer of 2026. I have confidence in doing so due to the experience that I have accrued over two MSc programmes and 5 years of work experience in data science. I am currently engaged in several methods courses on the MSc Applied Social Data Science program which should put me in a position to engage immediately, both methodologically and substantively.

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Appendix A: A Summary of Potential Feature Variables

Concept	Prior Research	Sub-concepts	Potential Data Sources	Unit of Analysis
Level of Democracy	Bowlsby et al., 2020; Collier & Hoeffler, 2004; Fearon & Laitin, 2003; Gelpi & Avdan, 2018; Gurses & Mason, 2010; Hegre, 2014; Hegre & Sambanis, 2006; McLaughlin et al., 1998, Vreeland, 2008	1. Polity Score, 2. Democracy Index	1. Polity5 2. Economist Democracy Index	National
Political Instability and Consistency	Eckstein, 1973; Galtung & Höivik, 1971; Hegre et al., 2013; Singer, 1972; Regan & Bell, 2010; Shellman, Levy, Young, 2013; Vreeland, 2008	1. Polity age, 2. Polity score transitions	1. Polity5 2. ACLED	National
Political Systems	De Mesquita, Siverson, Woller, 1992; Maoz & Abdolali, 1989; Marshall & Gurr, 2020; Muchlinski et al., 2015; Park, 2018	1. Polity characteristics	1. Polity5	National
Neighbourhood Political Economy and Activity	Collier & Hoeffler, 2004; Hegre & Sambanis 2006; Muchlinski et al., 2015; Østby, Nordås, Rød, 2009; Phillips, 2015; Rüegger, 2017	1. Presence of warring neighbour states, 2. neighbourhood political economy	1. IISG 2. IQSS 3. Geohive 4. SESHAT	Regional
National Geography	De la Calle & Sánchez-Cuenca, 2012; Gordillo, 2018; Hegre & Sambanis 2006; Stephenne, Burnley, Ehrlich, 2009	1. Terrain characteristics, 2. Territorial disputes	1. Center for Geographic Analysis (Harvard) 2. IROWS	National & Sub-national
Resources	Collier & Hoeffler, 2004; Collier, Hoeffler, Rohner, 2009; Hegre & Sambanis, 2006; Marks, 2019; Muchlinski et al., 2015	1. Presence of oil, 2. Availability of weapons, 3. Primary export %	1. PREC 2. IQSS 3. Center for Geographic Analysis (Harvard)	National & Sub-national
Religion	Maoz & Henderson, 2020	1. Religious heterogeneity	1. CHIA 2. PREC 3. SESHAT	National

Ethnicity	Cederman, Gleditsch, Wucherpfennig, 2018; Esteban, Mayoral, Ray, 2012; Fearon & Laitin, 2003; Hegre & Sambanis, 2006; Muchlinski et al., 2015; Sambanis, 2001	1. Ethnic heterogeneity	1. CHIA 2. EPR 3. PREC 4. SESHAT	National & Sub-national
Population	Thayer, 2009	1. Population aged 15-29 and male, 2. Population growth	1. CHIA 2. GGDC 3. IISG 4. UNDP 5. UND 6. SESHAT	National
Economics	Hegre et al., 2016; Piazzi, 2007; Polachek & Sevastianova, 2012; Tanaka, Tago, Gleditsch, 2017	1. Economic growth, 2. GDP per capita, 3. PPP	1. CHIA 2. CGEH 3. IEP 4. UNDP 5. World Bank 6. SESHAT	National
Militarisation	Lankford, 2011; Phillips, 2015	1. Military strength of state	1. Global Firepower 2. SIPRI Military Expenditure 3. CHIA	Regional, National & Sub-national
Connectivity	Fatehkia, Kashyap, Ingmar, 2018; Howard et al., 2011; Wolfsfeld, Segey, Sheafer, 2013	1. Internet penetration %	1. Facebook Advertising data	National & Sub-national
Temporality	Muchlinski et al., 2015; Mueller & Rauh, 2022	1. Previous conflict, 2. Previous polity score transition	1. UNHCR & FICSS 2. SESHAT	Regional, National & Sub-national
Refugees	Fisk, 2020; Zhou & Shaver, 2021	1. Presence of refugee camps, 2. Magnitude of presence, 3. Distance	1. UNHCR & FICSS	Sub-national
Actors	Cardenas. Gleditsch, Guevara, 2018; Cederman, Gleditsch, Wucherpfennig, 2018; Collier, Hoeffler, Rohner, 2009; Diehl,	1. Actor characteristics, 2. Actor behaviour	1. EPR 2. VDEM 3. UCDP Actor Dataset 4. SIENA	Regional, National & Sub-national

	1992; Gleditsch, Rivera, Zárate-Tenorio, 2022; Kalyvas, 2019			
Climate	Butler & Gates, 2012; Gleditsch, 2012; Nordås & Gleditsch, 2015; Koubi, 2019	1. Climate change	1. CAIT 2. UNECE	Regional, National & Sub-national
Events	Brandt et al., 2022; Hu et al., 2022; Mueller & Rauh, 2022; Raleigh et al., 2010, Zhou & Shaver, 2021	1. Magnitude of news on events prior, 2. Peace agreements, 3. Social Media sentiment, 4. Protests,	1. Newspapers, 2. ACLED, 3. GDELT, 4. UCDP Georeferenced dataset, 5. Social media, 6. Government documents, 7. PA-X: Peace Agreements, 8. UN Peacekeeper, 9. UCDP Violent Political Protest	National & Sub-national