Quantifying Heterogeneous Causal Treatment Effects in World Bank Aid Projects

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1 JZ abstract

The world bank funds aid projects in developing countries all over the world each year and about 5 trillion dollars have been allocated since 1945. Beside the evaluation of the project itself successful or not, it is important to know how the project have impact to the environment. In this paper, we achieve this by evaluating NDVI(Normalized Difference Vegetation Index) values. Inspired by the causal tree and causal forest methods proposed by Athey and Imbens, we investigate the heterogeneous causal effect of the world bank aid projects from 1982 to 2014. We observe that causal effect is greatly impact by geographic information such as countries or areas(where wars happened). We compared our result with economist model result(carbon estimation) and world bank IEG outcome.

Abstract. The world bank funds aid projects in third world countries all over the world each year. There is a natural interest in better understanding what makes a project succeed and what not. In technical terms, we are interested in estimating heterogeneity in causal effects and conduct inference about the magnitude of the differences in project effects across subsets of world bank projects. To do so, we analyze a data set with data on world bank projects from 1982 to 2014 that contains project characteristics, geographical, and environmental data such as temperature and precipitation. The key challenge for this analysis is that the observational data does not allow us to directly measure the difference between the result of performing a project and of not performing a project as reality only gives us the choice to do one of the two. Following recent research results by Athey and Imbens, we employ a combination of machine learning techniques such as random forests with techniques from causal inference to measure the average treatment effect, i.e. the average effect of a project, for subsets of geographic locations. We validate our findings with project evaluations from the world bank and outcomes of competing econometric models.

2 introduction

Some notes

- general problem in development: project has a time, space, and economic dimension,
- how to measure success
- how to measure what's going on
- how to measure impact (and when), how to infer causality
- problem present in particular in aid projects for third world
- describe data
- formulate research question that is addressed
- countries that have bad causal or good effects across different project starting years for the 5 continents
- figure show aid project in the world map
- main area or countries that have good or bad effects

Draw causal effects from data is one of the most interesting research problem across many disciplines. For example, people want to know the effects of a drug in medical studies, companies would like to know the effect of their advertisement on customers, government seeks to evaluate the effect of public policies, for our case, world bank wants to know the effect of the aid projects they investigate around the world over 30 years.
Instead of investigate the causal effects for the whole population, in this paper, we are interested in estimating heterogeneous causal effects for subpopulations by features or covariates. We can estimate heterogeneity by covariates on causal effects and then conducting inference for a distinct unit.
To avoid getting extreme treatment effects which lead to a spurious heterogeneous result, in disciplines such as clinical trial, they use pre-planed subgroup to analyze, for economic, they have pre-analysis plans for randomized experiments. With a data driven approach, the advantage is to discover some other causal effects instead of only the pre-planed subgroups.
To estimate heterogenous causal effects, there are several candidates, for example, classification and regression tree [4], random forest [3], LASSO [17], SVM [18] and so on. In this paper, we use the regression tree, the other methods such as random forest is also good candidate, but we focus on the regression tree in this paper.
In tradition, we can use decision trees to do prediction using the trained data or labeled data. We can build the regression tree to predicting the causal effects with the features as nodes in the tree. However, for the causal inference, the challenge is we do not have such data,in rubin causal model [9], we can only have the treated data or untreated data, but not both at the same time, hence we do not know the ground truth for prediction. We can't follow the traditional supervised machine learning method that we contract the tree with the trained the data and then use the the test data to do prediction based on the constructed tree. Follow the work of Athey and Imbens [1], we use causal tree to do heterogeneous causal effects estimation. However, in practice,for example in our case the world

bank data set, within a node, there maybe only treated or untreated data, we will discuss in the paper how to explain such data and other issues

- first analysis on heterogeneous causal effect of world bank aid projects using machine learning method
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3 methodology

3.1 conditional average treatment effects

Suppose we have a data set with n iid units with $i = 1, \cdots, n$, for each unit, it has a feature vector $X_i \in [0,1]^d$, a response $Y_i \in \mathbb{R}$ and treatment indicator $W_i \in \{0,1\}$.
For unit level causal effect, we can use Rubin causal model to estimate the average causal effect as shown in function 1,

$$\tau_i = Y_i(1) - Y_i(0) \tag{1}$$

In this paper, we are interested in heterogenous causal effect as 2, this estimator is proposed by [6],

$$\tau(x) = \mathbb{E}\big[Y_i(1) - Y_i(0) \mid X_i = x\big] \tag{2}$$

The challenge is we know either $Y_i(0)$ or $Y_i(1)$, but not both at the same time. We need to make a unconfoundness assumptions to estimate $\tau(x)$.

$$W_i \perp (Y_i(1), Y_i(0)) \mid X_i \tag{3}$$

Under the unconfoundness assumption, we can get the causal effect as

$$\tau(x) = \mathbb{E}\big[Y^* \mid X_i = x\big] \tag{4}$$

where Y^* is function 5, $e(x)$ is function 6, to estimate the propensity score, there are several ways for calculation such as [13], [8], in this paper, we use logic regression to calculate the pscore.

$$Y_i^* = Y_i^{obs} \cdot \frac{W_i - e(X_i)}{e(X_i) \cdot (1 - e(X_i))} \tag{5}$$

$$e(x) = \mathbb{E}\big[W_i \mid X_i = x\big] \tag{6}$$

3.2 Transformed Outcome Tree

The transformed outcomes tree is a regression tree with Y^* instead of Y. As mentioned above, the transformed outcome is calculated by 5, then we can use traditional regression tree method to estimate the causal effect as $\tau(x) = \mathbb{E}\big[Y^* \mid X_i = x\big]$

3.3 Causal Tree Model

We use regression tree to estimate the heterogeneous causal effects, the first step is to construct the tree. To construct the regression tree, we recursively partition the node until the size of the node is less than a threshold we set or the gain of split is negative.
In classic regression tree, mean square error (MSE) is often used to as the criterion for node splitting, the average value within the node is used as the estimator. Following Asthey and Imbens [1], we use 7 as the estimator and we calculate the error of the node by summing $Y_i^* - \hat{\tau}(X_i)$.

$$\hat{\tau}^{CT}(X_i) = \sum_{i:X_i \in \mathbb{X}_l} Y_i^{obs} \cdot \frac{W_i/\hat{e}(X_i)}{\sum_{i:X_i \in \mathbb{X}_l} W_i/\hat{e}(X_i)} - \sum_{i:X_i \in \mathbb{X}_l} Y_i^{obs} \cdot \frac{(1-W_i)/(1-\hat{e}(X_i))}{\sum_{i:X_i \in \mathbb{X}_l} (1-W_i)/(1-\hat{e}(X_i))} \tag{7}$$

3.4 Pruning the tree

To avoid overfitting of the tree, we need to prune the tree. We use the minimal cost complexity pruning and we define it as 8. α is the complexity parameter, with it we can construct the regression with the right size.

$$R_\alpha(T) = R(T) + \alpha \left|\tilde{T}\right| \tag{8}$$

where R(T) is the resubstitution error estimate of tree T, $\left|\tilde{T}\right|$ is defined as the complexity of the tree, which is the number of leaves in the tree,
To estimate the error of a node, we use function 9,

$$R(t) = \sum_{i=1}^{N} (Y_i - \hat{\tau}(X_i)) \tag{9}$$

where N is the total units in the nodes.

To get a sequence of α, we minimize function 10,

$$g(t, T) = \frac{R(t) - R(T_t)}{\left|\tilde{T}_t\right| - 1} \tag{10}$$

where T_t is a subtree of T rooted at node t.
We use the weakest link cutting to determine α and use it as the complexity parameter when we build the tree for the whole data set.
We use the train data set to construct the tree and then apply weakest link cutting to the tree with α starting with 0. Until there is one node in the tree, we get a series of α, $\alpha_0 < \alpha_1 < \cdots < \alpha_k$. Then we set $\beta_0 = 0$, $\beta_1 = \sqrt{\alpha_1 \alpha_2}$, $\cdots$, $\beta_{k-1} = \sqrt{\alpha_{k-1} \alpha_{know}}$

We use V-fold cross validation to estimate the errors for different β and use the β with minimum error. We divide the data into k sets randomly with the same size, we use $1, 2, 3, \cdots, v-1, k$ to represent the v-th data part and (k) as the left part of the data correspond to the v-th part. For each β_k, we useV-fold cross validation to get the estimated error. The error is calculated by function 11,

$$Err(\beta; Y_i^v, X_i^v) = \sum_1^N (Y_i^v - \hat{\tau}(X_i^{(v)})) \tag{11}$$

where $N = n/V$, n is the size of the whole data set. Then by using function 12, we can get the estimated error for each β value.

$$R(T(\beta)) = \frac{1}{V} \sum_1^V Err(\beta; Y_i^v, X_i^v) \tag{12}$$

3.5 Random forest with TOT trees

4 Data

4.1 Data sources and collection

We leverage the following data sources in this analysis:

4.2 Data pre-processing

This analysis uses three key types of data: satellite data to measure vegetation, data on the geospatial locations of World Bank projects, and covariate datasets (the sources of which are detailed above). Our primary variable of interest is the fluctuation of vegetation proximate to World Bank projects, which is derived from long-term satellite data (NASA 2015). There are many different approaches to using satellite data to approximate vegetation on a global scale, and satellites have been taking imagery that can be used for this purpose for over three decades. Of these approaches, the most frequently used is the Normalized Difference Vegetation Index (NDVI). The NDVI is a metric that has been used since the early 1970s, and is one of the simplest and most frequently used approaches to approximating vegetative biomass. NDVI measures the relative absorption and reflectance of red and near-infrared light from plants to quantify vegetation on a scale of -1 to 1, with vegetated areas falling between 0.2 and 1. The reflectance by chlorophyll is correlated with plant health, and multiple studies have illustrated that it is generally also correlated with plant biomass. In other words, healthy vegetation and high plant biomass tend to result in high NDVI values (Dunbar 2009). Using NDVI as an outcome measure has a number of other benefits, including the long and consistent time periods for which it has been calculated. While the NDVI does have a number of challenges - including a propensity to saturate over densely vegetated regions, the potential for atmospheric noise (including clouds) to incorrectly offset values, and reflectances from bright soils providing misleading estimates - the popularity of this measurement

Variables	Description	Source
ForestCover	NASA Long Term Data Record measurements of vegetative cover	http://ltdr.nascom.nasa.gov/cgi-bin/ltdr/ltdrPage.cgi
WorldBankProjectLocations	Double-blind geocoded information on the geographic location of each World Bank project	http://aiddata.org/level1/geocoded/worldbank
DistancetoRivers	The calculated average distance to all rivers	http://hydrosheds.cr.usgs.gov/index.php
DistancetoCommercialRivers	Calculated average distance to all commercial rivers	http://hydrosheds.cr.usgs.gov/index.php
DistancetoRoads	Distance to nearest road	http://sedac.ciesin.columbia.edu/data/set/groads-global-roads-open-access-v1
Elevation	Elevation data measured from the Shuttle Radar Topography Mission	http://www2.jpl.nasa.gov/srtm/
Slope	Slope data calculated based on the Shuttle Radar Topography Mission	http://www2.jpl.nasa.gov/srtm/
AccessibilitytoUrbanAreas	European Commission Joint Research Centre estimation of urban travel times.	http://forobs.jrc.ec.europa.eu/products/gam/download.p
PopulationDensity	Center for International Earth Science estimation of population density, derived from Nighttime Lights	http://sedac.ciesin.columbia.edu/data/collection/gpw-v3
AirTemperature	University of Delaware Long term, global temperature data interpolated from weather station measurements.	http://climate.geog.udel.edu/ climate/
Precipitation	University of Delaware Long term, global precipitation data interpolated from weather station measurements.	http://climate.geog.udel.edu/ climate/

has led to a number of improvements over time to offset many of these errors. This is especially true of measurements from longer-term satellite records, such as those used in this analysis, produced from the MODIS and AVHRR satellite platforms (NASA 2015).

The second primary dataset used in this analysis measures where - geographically - World Bank projects were located. This dataset was produced by AidData (2016), relying on a double-blind coding system where two experts employ a defined hierarchy of geographic terms and independently assign uniform latitude and longitude coordinates, precision codes, and standardized place names to each geographic feature. If the two code rounds disagree, the project is moved into an arbitration round where a geocoding project manager reconciles the codes to assign a master set of geocodes for all of the locations described in the available project documentation. This approach also captures geographic information at several levels?coordinate, city, and administrative divisions?for each location, thereby allowing the data to be visualized and analyzed in different ways depending upon the geographic unit of interest. Once geographic features are assigned coordinates, coders specify a precision code that varies from 1 (exact point) to 9 (national-level project or program). AidData performs many procedures to ensure data quality, including de-duplication of projects and locations, correcting logical inconsistencies (e.g. making sure project start and end dates are in proper order), finding and correcting field and data type mismatches, correcting and aligning geocodes and project locations within country and administrative boundaries, validating place names and correcting gazetteer inconsistencies, deflating financial values to constant dollars across projects and years (where appropriate), strict version control of intermediate and draft data products, semantic versioning to delineate major and minor versions of various geocoded datasets, and final review by a multidisciplinary working group.

4.3 Data characteristics

- provide an overview of the total number of covariates and their characteristics
- Forest cover (= NDVI?): time series. As this is an important variable, can we get a box plot with mean values and slope values for all projects?
- for covariates, we should provide some outline about type (categorical, ordinal,numerical), ranges of values, and if some normalization is applied. If data gives a time series, its granularity (time and space), concerns about precision
- set of world bank projects covers a broad range of topics and individual projects do not necessarily directly target deforestation. We want to recognize projects that show an impact on forest cover, be it positive or negative.
- discuss projects and project locations: a project can take place at more than one geographic location. The data contains projects that have between 1 and 10 locations. This raises the question on how to aggregate average treatment effects across a set of project locations into a single value for the overall project.

4.4 Data interpretation for the context of measuring heterogenous treatment effects

- general idea is to separate data into treated and untreated cases, there is no particular notion of time. For each entity (treated or untreated), a set of covariates are provided.
- in our case: we decided to interpret the project start as the treatment and the change in forest cover (average?, slope?) as the treatment effect.
- as we only have data for locations were a project takes place, we consider small scale projects with small amounts of funding as untreated cases (???)
- We decided for time series data: split into two parts, before and after project start. We only take covariates for data before project starts into account for selecting variables in the random forest construction. We use data after the project starts to compute treatment effects. Rationale: covariates with data

after treatment may be correlated with the outcome which would corrupt the calculation of average treatment effects (?).
- Since large scale correlations and changes beyond the reach of the project such as the beginning or ending of a draught period over several years may by hiding within time series data, we decided to compare projects that all started in the same year in order to have level playing field for projects in the same geographic region.

4.5 Calculation of Propensity Scores

- describe how we calculate propensity scores before we feed the data into a random forest

5 experiments

In 2004, there are totally 114 projects contain 1628 subproject in different locations.

5.1 causal tree,TOT tree and TOT tree based random forest

Our method is based on the R package rpart [16]. Rpart support user defined split function, therefore, we can use the split criterion function 7. To improve the efficiency of the r program, we use rcpp and call C++ functions inside the split and evaluation function for each node in the tree. To further improve the c++ functions, we use openmp inside the C++ functions. To avoid the extreme cases, such as only treated or untreated data in the internal nodes, we would not split under in such condition.

We use the randomForest [10] R package to build the forest.

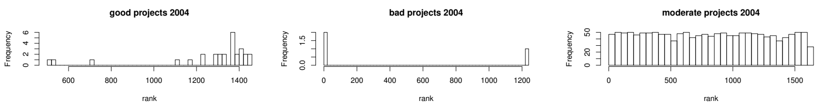
5.2 random forest with TOT trees

- variable importance, important variables should be in the top levels of the tree, important to the causal effects
- regression variability, interval, in a forest, how stable the effect of a project is, if the variance is small, we can trust the result
- validate the result, one of the challenges is we do not have golden truth for the projects, we have partial result from world bank IEG which is for the assessment of the implement of the overall projects, as each projects usually have more than two sub projects on different locations, the estimation is coarse. Another source of result is from the economist result, based on these two evaluation, we can validate our work to some extent.
- About 83% projects in 2004 have more than 1 locations, the IEG outcomes take all of the them as a whole, in our random forest, we have causal results for sub projects, hence, one project may have both good and bad causal effects.

Europe				Aisa				South America				Africa			
Country	CT	TOT	RF	Country	CT	TOT	RF	Country	CT	TOT	RF	Country	CT	TOT	RF

project ID(total 1628)	random forest estimation(low to high)	world bank result	economist result(4271)
P076924	6 ,21,1179	Highly Unsatisfactory	NA()
P082914	484,545	Highly satisfactory	499, 501, 654, 684 ,750, 954
P074872	711,1085 ,1182, 1224 ,1230 ,1288, 1291, 1308, 1313 ,1324, 1333, 1360, 1366, 1367, 1376, 1378 , 1379, 1383, 1396, 1400, 1403, 1417, 1429, 1434, 1443	Highly satisfactory	??
P075387	1463	Highly satisfactory	NA

- quantile for each project location, variability of the causal effects, uncertainty of the result, 8% data have all causal effects have same effect, either positive or negative result, 90% have either positive or negative result from quantile 25% to 75%



(a) good projects rank (b) bad projects rank (c) moderate projects rank

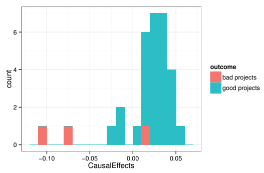
Fig. 1: original data without considering quantile

5.3 new data set

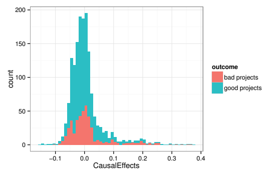
Instead of the old data set with time series covariates, we establish the new data set which is the subset of the whole projects, which share the same project starting year, the starting years is between 2000 to 2012, project that started at 2000 has the largest number. We use projects start at 2000 to build the new data set.
In the new data set, we transform the time series covariate to the trend before the projects started and the trend after the project started along with the covariates with no time series. Then we use cross validation to choose the optimal complexity parameter and then use it to the new data set.

5.4 interpretation of results

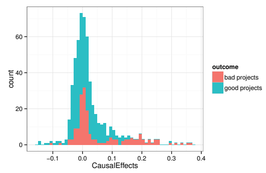
- Interpretation of data, what can we get out of the random forest?



(a) Highly Sat vs Highly Unsat

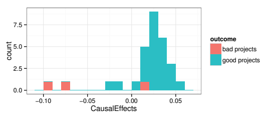


(b) Highly Sat, Sat vs Highly Unsat, Unsat

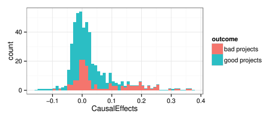


(c) Highly Sat, Sat, Moderately Sat vs Highly Unsat, Unsat, Moderately Unsat

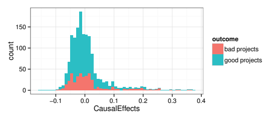
Fig. 2: original data without considering quantile



(a) Highly Sat vs Highly Unsat

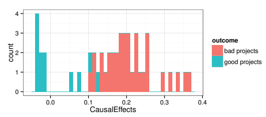


(b) Highly Sat, Sat vs Highly Unsat, Unsat

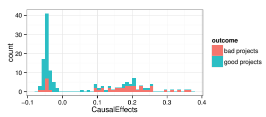


(c) Highly Sat, Sat, Moderately Sat vs Highly Unsat, Unsat, Moderately Unsat

Fig. 3: data with causal effect quantile from $25\% - 50\%$ without cross 0



(a) Highly Sat, Sat vs Highly Unsat, Unsat



(b) Highly Sat, Sat, Moderately Sat vs Highly Unsat, Unsat, Moderately Unsat

Fig. 4: data with causal effect quantile from $0\% - 100\%$ without cross 0

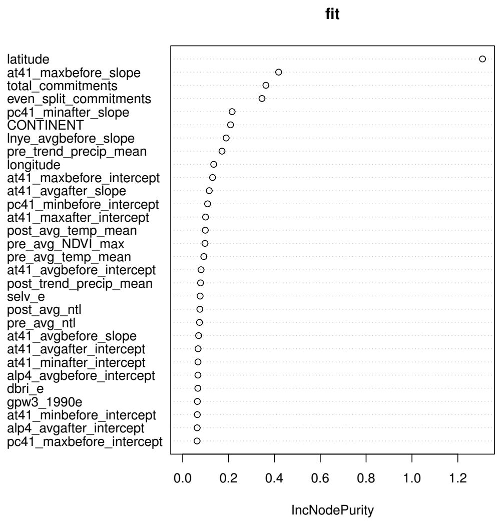


Fig. 5: variable importance 2004 projects

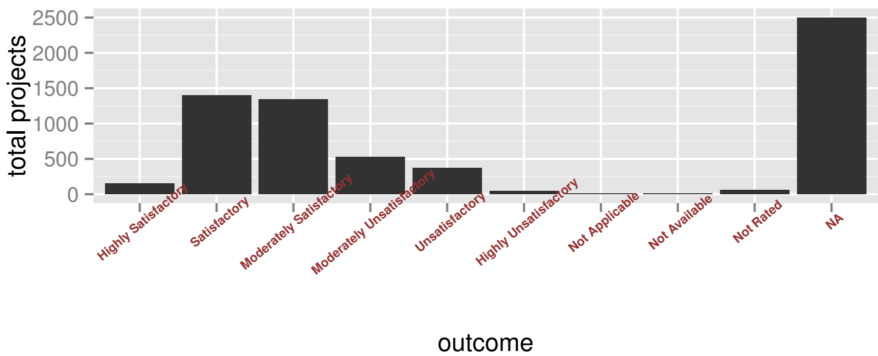


Fig. 6: IEG outcome overview

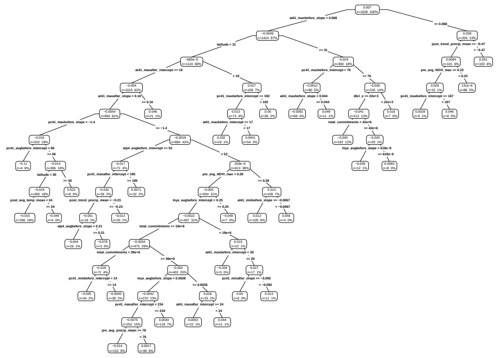


Fig. 7: causal tree of projects in 2004

- Anecdotal evidence, discuss best and worst project, what is it about, what happens here.
- Numerical values for CATE? What is the exact interpretation of the calculated values (difficult thanks to propensity score weighting), but estimate of average should have a direct interpretation right? Interpret value for best and worst project.
- Ranking of projects with respect to CATE?
- Selection of variables / covariates are commonly selected among trees in the random forest? Provide details, interpret results. E.g. geographic location, show maps.
- Comparison with an econometric model that looks at carbon foot print(?)
- Comparison with a world bank project evaluation from a human resources point of view

6 related work

Causality [12] plays an important role in many area. In this paper, we focus on the heterogeneous causal effects. Some paper in the literature use tree based machine learning technique to estimate heterogeneous causal effects. In [14], they use statistical test as the criterion for node splitting. In [1], they use causal trees to estimate heterogeneous treatment effect. However, they do not show what if in some nodes, there is only treated units or only untreated units and then how to estimate the heterogeneous causal effects.
Some paper use forest based machine learning technique to estimate heterogeneous causal effects. In [19], they use casual forest to do heterogeneous causal

effects estimation, and they share the same idea in paper [5] that they use difference data for the structure of the tree and the estimation value within each node.
In [15], they change the item image size on ebay and observer the treatment effect as how much money people spent during the experiment. The difference between their work and ours is that they only change one factor, however, for aid data, a project may change several factor which is more complex compared to IT data. [7] Regression random forest can give estimation of the conditional means, in [11], they use quantile regression forest to estimate the distribution of the result instead of mean and they prove the algorithm is consistent. As discussed in [2], [20], , [5], there is a gap between theory property and practical use of random forest.

7 Conclusions

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