Poverty Mapping in Off-Census Years

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Introduction

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- In what follows, we'll discuss this modern approach in more detail and work through a simple application.

An Example

RESEARCH ARTICLE | ECONOMIC SCIENCES

Microestimates of wealth for all low- and middle-income countries

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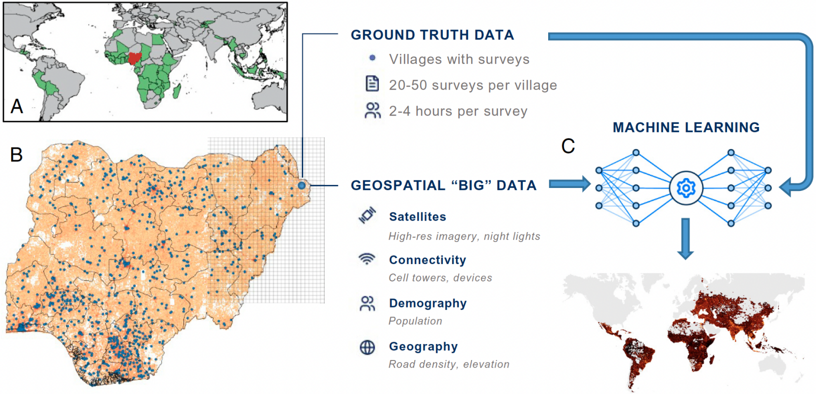
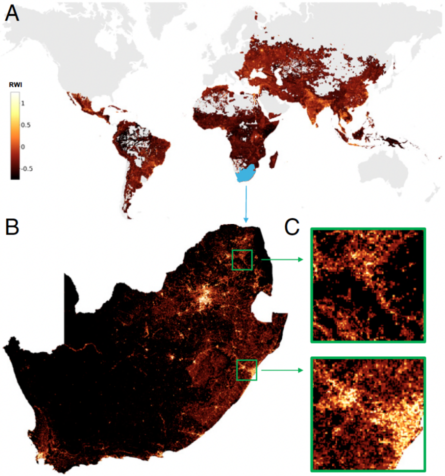
An Example



A
B
GROUND TRUTH DATA
Villages with surveys
20-50 surveys per village
2-4 hours per survey
GEOSPATIAL "BIG" DATA
Satellites
High-res imagery, night lights
Connectivity
Cell towers, devices
Demography
Population
Geography
Road density, elevation
C
MACHINE LEARNING

An Example



Machine Learning

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  2. Supervised learning: Uses a set of features to predict some outcome of interest
- Supervised learning can be further divided into regression and classification tasks:
  1. Regression: Concerned with predicting continuous outcomes
  2. Classification: Focuses on predicting categorical outcomes

Machine Learning

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- Gradient boosting machines combine a large number of weak "learners" to form a stronger "ensemble" prediction:
  - Models are added to the ensemble sequentially by fitting new learners to the negative gradient of the loss function.
  - With a squared-error loss function, this amounts to sequentially fitting new models to the current residuals of the ensemble.

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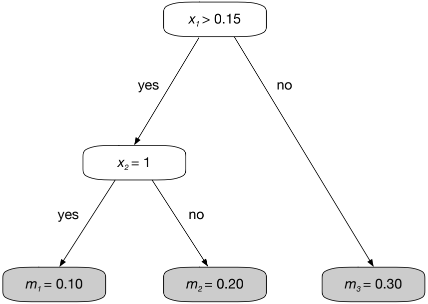
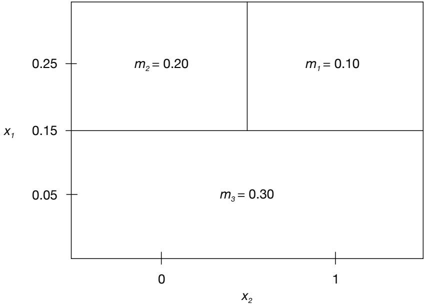
- Extreme gradient boosting (XGBoost) is a particularly popular implementation that uses classification and regression trees as the base models.

Machine Learning



(a) Regression tree



(b) Covariate space

Machine Learning

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- XGBoost uses the following specification for the regularization term:

$$r(f_t) = \gamma M_t + \frac{1}{2}\lambda \sum_j m_{tj}^2$$

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- XGBoost instead seeks to minimize the objective function by greedily optimizing one level of the tree at a time:
  1. For a given node, calculate the reduction in the objective function for every possible split rule for every available covariate.
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- XGBoost continues splitting nodes until some user-specified stopping rule is met.

Machine Learning

- Like many machine-learning models, XGBoost relies on various hyperparameters that must be selected by the user:
  - The regularization term (i.e., γ and λ)
  - Maximum tree depth and number of trees
  - Feature subsampling
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- There are several different ways one might approach hyperparameter selection:
  - Use the default hyperparameters
  - Grid search
  - Bayesian hyperparameter optimization

An Application

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  - Direct poverty estimates for a subset of areas
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- For a simple application, we'll use the 2015 Mexican Intercensal Survey (MIS) for both data sources:
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  - Representative at the national, state, and municipality level
  - Gathered information on household income, location, demographics, etc.
- We'll treat the MIS as if it were a real census and use it to simulate the data used for poverty maps in off-census years:
  - Sample households from the MIS to obtain direct poverty estimates for a subset of municipalities.
  - Collapse the micro-data to the municipality level to obtain area-level covariates.

An Application

municipality	direct	true	hhsize	age_hh	male_hh	piped_water	no_piped_wate	no_sewage	sewage_pub
1011001	0.0731939	0.0792447	−0.392702	−0.656265	−0.327982	0.713719	−0.703915	−0.776471	1.31692
1011002	0.311203	0.262542	1.16187	−0.751027	0.693776	0.687339	−0.683918	−0.444965	0.983853
1011003	0.231818	0.243805	0.249574	0.0228985	0.326906	0.709911	−0.698422	−0.764816	1.19186
1011004	0.182292	0.246614	1.39054	−0.284892	1.05251	0.760751	−0.762797	−0.701359	1.32361
1011005	0.0783132	0.0922531	0.223972	−1.61063	0.866597	0.695103	−0.689421	−0.769329	1.22863
1011006	0.145161	0.142484	0.767608	−0.98952	−0.0114516	0.678938	−0.670958	−0.72303	1.24327
1011007	0.365188	0.239514	1.35238	−0.888183	0.294417	0.675333	−0.678623	−0.667009	1.23939
1011008	0.212766	0.207656	0.977491	−1.11958	−0.69044	0.636178	−0.624729	−0.560338	1.19124
1011009	0.224299	0.228771	0.798937	−0.761821	1.27636	0.705323	−0.693837	−0.660832	1.18033
1011010	0.230769	0.236398	0.740872	−0.791986	1.41223	0.565258	−0.553847	−0.424855	0.884507
1011011	0.08	0.107069	−0.297909	−2.6176	0.715367	0.717107	−0.705614	−0.783883	1.35315
1021001	0.0316456	0.0720229	−1.41713	−1.37729	−1.40387	−0.0613733	0.0676727	−0.166492	0.0262108
1021002	0.127098	0.0514764	−1.53969	−1.3291	−0.777536	0.598097	−0.591137	−0.548799	0.956378
1021003	0.0377359	0.053013	−1.19462	−1.31876	−1.1787	0.135678	−0.137525	−0.644508	0.553619
1021004	0.0105125	0.0438967	−1.35347	−1.54744	−1.15381	0.54075	−0.534839	−0.663636	1.10457
1021005	nan	0.0627038	−1.09161	−1.20586	−1.1212	−0.0864749	0.06466	−0.66397	0.0944137
1031001	0.0664452	0.0982665	−1.55223	−0.407757	−0.48133	0.333902	−0.339917	−0.438449	0.33179

An Application

```python
# Import libraries
import xgboost as xgb
import pandas as pd

# Set directory
path = '/Users/hendersonhl/Desktop/Summer University/Application/'

# Import data
data = pd.read_csv(path + 'data.csv', header = 0)
sample = data.dropna()
y = sample['direct']
X = sample.drop(columns = ['municipality', 'direct', 'true'])

# Implement XGBoost
model = xgb.XGBRegressor(objective='reg:squarederror', n_estimators=100,
        max_depth=6, eta=0.3)
model.fit(X, y)

# Generate poverty estimates
X_all = data.drop(columns = ['municipality', 'direct', 'true'])
y_pred = model.predict(X_all)
```

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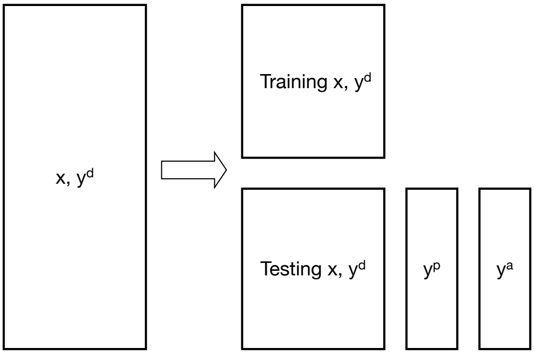

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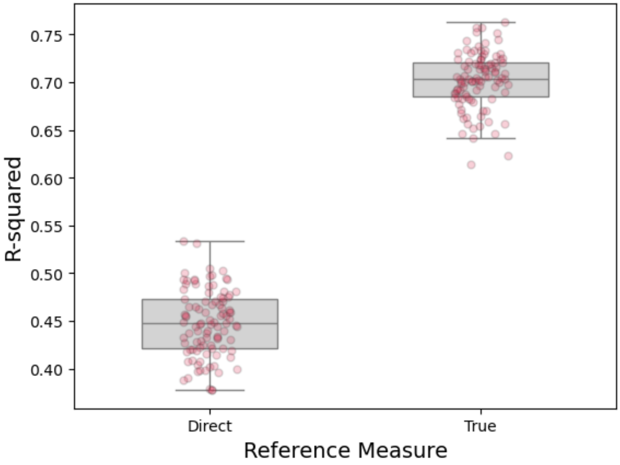
```python
# Import additional functions
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score

# Create empty lists
r2_direct = []
r2_true = []

# Run loop
for i in range(100):
    # Split data and fit model
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5)
    model.fit(X_train, y_train)
    # Get predicted and true values
    y_pred = model.predict(X_test)
    y_true = [sample['poor'][i] for i in y_test.index]
    # Save R-squared results
    r2_direct.append(r2_score(y_test, y_pred))
    r2_true.append(r2_score(y_true, y_pred))
```

An Application



Resources

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