

MCW Biostatistics Technical Report 67: Predicting Left Ventricular Hypertrophy (LVH) with Bayesian Additive Regression Trees (BART)

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In this technical report, we provide R users with the ability to predict Left Ventricular Hypertrophy (LVH) using ECG and subject data with Bayesian Additive Regression Trees (BART). You will find these files in a ZIP archive online at <https://www.mcw.edu/-/media/MCW/Departments/Biostatistics/tr067.zip>. You will also need the BART R package which you can find online at <https://cran.r-project.org/package=BART>. The R program is `tr067.R`. Two prediction models are presented: BART-LVH and an ECG-only sub-model, BART-LVH ECG-only. BART-LVH is preferable since it has slightly better performance than BART-LVH ECG-only in R^2 and Sensitivity. From here on, we denote these models by the number of covariates used to predict the outcome. BART-LVH is BART26 utilizing 26 covariates with ECG data, gender, age, height and SBP/DBP; and BART-LVH ECG-only is BART22 using 22 covariates from ECG data and gender but excludes age, height and SBP/DBP.

The BART26 and BART22 models predict Normalized Left Ventricular Mass (LVM) expressed mathematically as $y_i \sim N(f(\mathbf{x}_i), w_i^2 \sigma^2)$ with predictors \mathbf{x}_i where $f \stackrel{\text{prior}}{\sim}$ BART. BART is a Bayesian nonparametric machine learning method. The BART function, f , is an ensemble sum of trees. These BART models were fitted and the trees from these fits are encoded in R objects: `bart26.rds` contains the details of the BART26 fit and `bart22.rds`, the BART22 fit. As you will see exemplified in the R program `tr067.R`, the R `predict` function can be used to generate predictions at new data points which are provided by an R matrix or an R data frame, e.g., `yhat=predict(bart26, x)`.

Normalized LVM has a heavier right tail than left, therefore, we have fitted BART with two weight values, w_i : 0.905 for values < 1.037 and 1.105 for values ≥ 1.037 . Based on body size, a mean value of the LVM was predicted using the following allometric formula previously derived from a MESA subpopulation of 822 men and women without LVH risk factors (`typewriter` font represents variable names found in the R data frames):

$$\text{exp_lvm} = c(\text{height in m})^{0.561}(\text{weight in kg})^{0.608} \text{ where } c = \begin{cases} 6.82 & \text{females} \\ 8.17 & \text{males} \end{cases}.$$

We define Normalized LVM as: `lvh_lvm = olvedm1/exp_lvm` where `olvedm1` is the LVM in grams as determined by cardiac magnetic resonance imaging (cMRI) which is estimated via BART as $\hat{y}_i = \hat{f}(\mathbf{x}_i)$. The 95% quantile for `lvh_lvm` is 1.31 so values ≥ 1.31 are indicative of LVH. However, this cutoff is at the prediction level, y_i , rather than at the mean level, $E[y_i] = f(\mathbf{x}_i)$; hence, 1.31 is too extreme. An appropriate cutoff for LVH by $f(\mathbf{x}_i)$ was determined to be 1.19 corresponding to the 93% quantile.

Table 1 is a list of the predictors and their units. To demonstrate the prediction process, we have supplied synthesized data based on the MESA study including the training, `mesa.train.rds`, and the validation, `mesa.test.rds`. So that these subjects can not be identified, a 5% error was added to the continuous variables and 5% of the discrete variables were altered. This process is presented as a prescription that the user can follow with their own data to make LVM and LVH predictions with the BART models.

The following results were generated by running the R program `tr067.R` which loads the data and computes statistical summaries and graphics files. In Table 2, we summarize R^2 between cMRI LVM and the BART predictions. In Table 3, we present contingency tables between cMRI LVH and the BART predictions. Furthermore, the generated Figures are presented as well where the red dots are females and the blue dots are males.

Table 1: Table of predictors used to estimate Normalized Left Ventricular Mass. Predictors denoted by an asterisk (*) are included with BART26 but excluded from BART22.

Predictors	Description
samv21	S amplitude lead V ₂ , μV
hearttrt1	heart rate, bpm
sbp1c*	systolic blood pressure, mmHg
ppdrv21	P' duration lead V ₂ , ms
tamv61	T amplitude lead V ₆ , μV
ramv41	R amplitude lead V ₄ , μV
pdurv41	P duration lead V ₂ , ms
qrsdur1	QRS duration, ms
stjv41	STJ amplitude lead V ₄ , μV
ramv11	R amplitude lead V ₁ , μV
age1c*	age, years
samv11	S amplitude lead V ₁ , μV
ramav11	R amplitude lead aVL, μV
briv61	intrinsicoid deflection R wave lead V ₆
ramv51	R amplitude lead V ₅ , μV
tamv11	T amplitude lead V ₁ , μV
gender1	sex: 0=female, 1=male
htcm1*	height, cm
stjv21	STJ amplitude lead V ₂ , μV
samv31	S amplitude lead V ₃ , μV
ramv31	R amplitude lead V ₃ , μV
tamv41	T amplitude lead V ₄ , μV
dbp1c*	diastolic blood pressure, mmHg
tami1	T amplitude lead I, μV
ramavf1	R amplitude lead aVF, μV
stjv11	STJ amplitude lead V ₁ , μV

Table 2: R^2 between cMRI LVM and the BART predictions

Set	BART26		BART22	
	Normalized LVM	LVM	Normalized LVM	LVM
Training	40.2%	72.9%	35.2%	70.9%
Validation	24.8%	65.3%	20.0%	62.9%

Table 3: Contingency table of cMRI LVH and the BART predictions

Set	cMRI	BART26			BART22		
		No LVH	LVH		No LVH	LVH	
Training	No LVH	3348	156	Spec.=95.5%	3363	141	Spec.=96.0%
	LVH	140	130	Sens.=48.1%	157	113	Sens.=41.9%
Validation	No LVH	821	48	Spec.=94.5%	837	32	Spec.=96.5%
	LVH	50	21	Sens.=29.6%	54	17	Sens.=23.9%















