

Model-Based Regression Trees in Economics and the Social Sciences

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Overview

- Motivation: Trees and leaves
- Methodology
 - Model estimation
 - Tests for parameter instability
 - Segmentation
 - Pruning
- Applications
 - Costly journals
 - Beautiful professors
 - Choosy students
- Software

Motivation: Trees

Breiman (2001, *Statistical Science*) distinguishes two cultures of statistical modeling:

Data models

- Stochastic models, typically parametric.
- Predominant modeling strategy in economics and social sciences.
- Regression models are workhorse for empirical analyses.

Algorithmic models

- Flexible models, data-generating process unknown.
- Example: Regression trees model dependent variable *Y* by "learning" a partition w.r.t explanatory variables Z_1, \ldots, Z_l .
- Few applications in social sciences and especially in economics.

Motivation: Leaves

Examples for trees: CART and C4.5 in statistical and machine learning, respectively.

Key features: Predictive power in nonlinear regression relationships, *and* interpretability (enhanced by visualization), i.e., no "black box".

Typically: Simple models for univariate *Y*, e.g., mean or proportion.

Idea: More complex models for multivariate Y, e.g., multivariate normal model, regression models, etc.

Here: Synthesis of parametric data models and algorithmic tree models.

Recursive partitioning

Base algorithm:

- Fit model for Y.
- 2 Assess association of Y and each Z_j .
- Split sample along the Z_{i*} with strongest association: Choose breakpoint with highest improvement of the model fit.
- Repeat steps 1–3 recursively in the subsamples until some stopping criterion is met.

Here: Segmentation (3) of parametric models (1) with additive objective function using parameter instability tests (2) and associated statistical significance (4).

1. Model estimation

Models: $\mathcal{M}(Y, \theta)$ with (potentially) multivariate observations $Y \in \mathcal{Y}$ and *k*-dimensional parameter vector $\theta \in \Theta$.

Parameter estimation: $\hat{\theta}$ by optimization of objective function $\Psi(Y, \theta)$ for *n* observations Y_i (i = 1, ..., n):

$$\widehat{\theta} = \operatorname{argmin}_{\theta \in \Theta} \sum_{i=1}^{n} \Psi(Y_i, \theta).$$

Special cases: Maximum likelihood (ML), weighted and ordinary least squares (OLS and WLS), quasi-ML, and other M-estimators.

Central limit theorem: If there is a true parameter θ_0 and given certain weak regularity conditions, $\hat{\theta}$ is asymptotically normal with mean θ_0 and sandwich-type covariance.

2. Tests for parameter instability

Estimating function: Model deviations can be captured by

$$\psi(\mathbf{Y}_{i},\widehat{\theta}) = \frac{\partial \Psi(\mathbf{Y},\theta)}{\partial \theta} \Big|_{\mathbf{Y}_{i},\widehat{\theta}}$$

Fluctuation tests: Systematic changes in parameters over the variables $Z = (Z_1, ..., Z_l)$ can be assessed by fluctuations in empirical estimating functions.

- Andrews' supLM test for numerical Z_j,
- χ^2 -type test for categorical Z_j .

3. Segmentation

Goal: Split model into b = 1, ..., B segments along the partitioning variable Z_j associated with the highest parameter instability. Local optimization of

$$\sum_{b}\sum_{i\in I_{b}}\Psi(Y_{i},\theta_{b}).$$

Here: B = 2, binary partitioning.

4. Pruning

Pruning: Avoid overfitting.

Pre-pruning: Internal stopping criterion. Stop splitting when there is no significant parameter instability.

Post-pruning: Grow large tree and prune splits that do not improve the model fit (e.g., via crossvalidation or information criteria).

Here: Pre-pruning based on Bonferroni-corrected *p* values of the fluctuation tests.

Costly journals

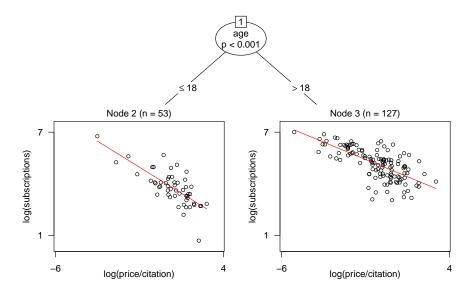
Task: Price elasticity of demand for economics journals.

Source: Bergstrom (2001, *Journal of Economic Perspectives*) "Free Labor for Costly Journals?", used in Stock & Watson (2007), *Introduction to Econometrics*.

Model: Linear regression via OLS.

- Demand: Number of US library subscriptions.
- Price: Average price per citation.
- Log-log-specification: Demand explained by price.
- Further variables without obvious relationship: Age (in years), number of characters per page, society (factor).

Costly journals



Costly journals

Recursive partitioning:

	Regressors		Partitioning variables				
	(Const.)	log(Pr./Cit.)	Price	Cit.	Age	Chars	Society
1	4.766	-0.533	3.280	5.261	42.198	7.436	6.562
	< 0.001	< 0.001	0.660	0.988	< 0.001	0.830	0.922
2	4.353	-0.605	0.650	3.726	5.613	1.751	3.342
	< 0.001	< 0.001	0.998	0.998	0.935	1.000	1.000
3	5.011	-0.403	0.608	6.839	5.987	2.782	3.370
	< 0.001	< 0.001	0.999	0.894	0.960	1.000	1.000

(Wald tests for regressors, parameter instability tests for partitioning variables.)

Task: Correlation of beauty and teaching evaluations for professors.

Source: Hamermesh & Parker (2005, *Economics of Education Review*). "Beauty in the Classroom: Instructors' Pulchritude and Putative Pedagogical Productivity."

Model: Linear regression via WLS.

- Response: Average teaching evaluation per course (on scale 1–5).
- Explanatory variables: Standardized measure of beauty and factors gender, minority, tenure, etc.
- Weights: Number of students per course.

	All	Men	Women
(Constant)	4.216	4.101	4.027
Beauty	0.283	0.383	0.133
Gender (= w)	-0.213		
Minority	-0.327	-0.014	-0.279
Native speaker	-0.217	-0.388	-0.288
Tenure track	-0.132	-0.053	-0.064
Lower division	-0.050	0.004	-0.244
R ²	0.271	0.316	

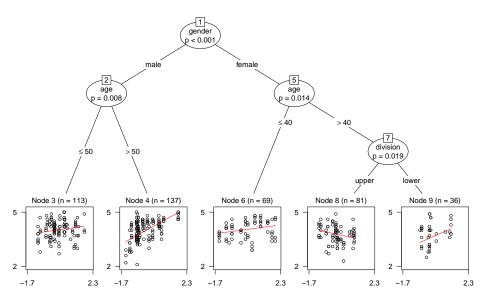
(Remark: Only courses with more than a single credit point.)

Hamermesh & Parker:

- Model with all factors (main effects).
- Improvement for separate models by gender.
- No association with age (linear or quadratic).

Here:

- Model for evaluation explained by beauty.
- Other variables as partitioning variables.
- Adaptive incorporation of correlations and interactions.



Recursive partitioning:

	(Const.)	Beauty
3	3.997	0.129
4	4.086	0.503
6	4.014	0.122
8	3.775	-0.198
9	3.590	0.403

Model comparison:

Model	R ²	Parameters
full sample	0.271	7
nested by gender	0.316	12
recursively partitioned	0.382	10 + 4

Choosy students

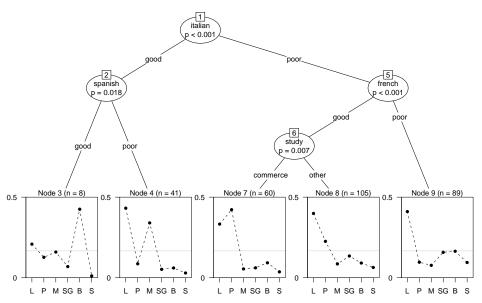
Task: Choice of university in student exchange programmes.

Source: Dittrich, Hatzinger, Katzenbeisser (1998, *Journal of the Royal Statistical Society C*). "Modelling the Effect of Subject-Specific Covariates in Paired Comparison Studies with an Application to University Rankings."

Model: Paired comparison via Bradley-Terry(-Luce).

- Ranking of six european management schools: London (LSE), Paris (HEC), Milano (Luigi Bocconi), St. Gallen (HSG), Barcelona (ESADE), Stockholm (HHS).
- Interviews with about 300 students from WU Wien.
- Additional information: Gender, studies, foreign language skills.

Choosy students



Choosy students

Recursive partitioning:

	London	Paris	Milano	St. Gallen	Barcelona	Stockholm
3	0.21	0.13	0.16	0.07	0.43	0.01
4	0.43	0.09	0.34	0.05	0.06	0.03
7	0.33	0.42	0.05	0.06	0.09	0.04
8	0.40	0.23	0.09	0.13	0.09	0.06
9	0.41	0.10	0.08	0.16	0.16	0.09

(Standardized ranking from Bradley-Terry model.)

Software

All methods are implemented in the R system for statistical computing and graphics. Freely available under the GPL (General Public License) from the Comprehensive R Archive Network or from R-Forge:

- Trees/recursive partytioning: party,
- Structural change inference: strucchange,
- Bradley-Terry regression/tree: prefmod2, psychotree.

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http://www.R-project.org/
http://CRAN.R-project.org/
http://R-Forge.R-project.org/
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Summary

Model-based recursive partitioning:

- Synthesis of classical parametric data models and algorithmic tree models.
- Based on modern class of parameter instability tests.
- Aims to minimize clearly defined objective function by greedy forward search.
- Can be applied general class of parametric models.
- Alternative to traditional means of model specification, especially for variables with unknown association.
- Object-oriented implementation freely available: Extension for new models requires some coding but not too extensive if interfaced model is well designed.

References

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