SUPPLEMENT TO

The potential of model-based recursive partitioning in the social sciences – Revisiting Ockham's Razor

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This supplement¹ is designed to illustrate applications of classification and regression trees as well as model-based recursive partitioning in the freely available software R (R Development Core Team 2009; see, e.g., Dalgaard 2002, for a general introduction to R).

The examples presented in this supplement are similar in spirit to the examples presented in the chapter, but simulated data are used. For terms to access the German Socio-Economic Panel Study (SOEP) from 2008, provided by DIW Berlin (German Institute for Economic Research), visit http://www.diw.de/.

Preliminary settings

• Upload the file example_data.RData (an active internet connection is necessary)

```
> load(url("http://www.statistik.lmu.de/~kopf/example_data.RData"))
The file contains three data sets, namely dat_empl, dat_unempl, dat_job.
```

• Inspect data structure, e.g. for dat_empl containing gender, age, job_time

```
> names(dat_empl)
```

```
[1] "gender" "age" "job_time"
```

```
> head(dat_empl)
```

```
gender age
              job_time
1
   male 31
                 other
2
   male
          53 full time
3
   male
          36
                 other
4
          57 full time
   male
5
   male
          59
                 other
   male 20
6
                 other
```

```
> str(dat_empl)
```

```
'data.frame': 19553 obs. of 3 variables:
$ gender : Factor w/ 2 levels "male","female": 1 1 1 1 1 1 1 1 1 1 ...
$ age : num 31 53 36 57 59 20 41 57 42 38 ...
$ job_time: Factor w/ 2 levels "full time","other": 2 1 2 1 2 2 1 1 1 2 ...
```

```
> summary(dat_empl)
```

¹This document was created with Sweave to combine IAT_EX and R code (Leisch 2002).

gender job_time age male : 9318 Min. :18.00 full time: 7404 female:10235 1st Qu.:33.00 :12149 other Median :48.00 Mean :45.98 3rd Qu.:62.00 :64.00 Max.

• Load package party (Hothorn, Hornik, & Zeileis 2006; Zeileis, Hothorn, & Hornik 2008) (if party has not yet been used, the install.packages() command allows to download the package)

```
> install.packages("party", dependencies=TRUE)
> library("party")
```

Classification tree

• Construct a classification tree for a binary response variable (here: job_time)

```
> ct_obj <- ctree(job_time ~ gender + age,
> control = ctree_control(minsplit = 50), data = dat_empl)
```

• Examine the resulting classification tree object

> ct_obj Conditional inference tree with 4 terminal nodes Response: job_time Inputs: gender, age Number of observations: 19553 1) gender == {male}; criterion = 1, statistic = 1910.231 2) age <= 62; criterion = 1, statistic = 1397.736 3)* weights = 6835 2) age > 624)* weights = 2483 1) gender == {female} 5) age <= 60; criterion = 1, statistic = 530.524 6)* weights = 7274 5) age > 607)* weights = 2961

Here, job_time is a binary response variable – indicating whether or not the respondent works full-time ("full time", "other") – whereas gender and age are potential splitting variables like in the example in section 2.1. Splitting variables can be of every commonly used covariate format (factor, ordered factor or numerical) as long as it is correctly specified in the software. The argument control = ctree_control() offers various options the user can specify: minsplit=50 requires at least 50 observations in a node to conduct a split. Alpha level, test statistics and distributive characteristics can be chosen as well (see ?ctree in R). • Plot the ctree-object

> plot(ct_obj, terminal_panel = node_barplot(ct_obj, beside=TRUE))

Calling plot(ct_obj) would result in a stacked bar plot, while the option terminal_panel = node_barplot(ct_obj, beside=TRUE) displays a vertical-bar chart such as in Figure 3.1 in the chapter.



Figure 3.1: Classification tree: Simulated data indicating frequencies of full-time jobs.

Regression tree

• Calculate a regression tree

```
> rt_obj <- ctree(take_job ~ gender + age + nation + marital,
> control = ctree_control(minsplit = 10), data =dat_unempl)
```

• Examine the resulting regression tree object

```
> rt_obj
```

Conditional inference tree with 4 terminal nodes

```
Response: take_job
Inputs: gender, age, nation, marital
Number of observations: 950
1) gender == {male}; criterion = 1, statistic = 115.915
2) age <= 43; criterion = 0.988, statistic = 8.841
3)* weights = 236</pre>
```

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```
2) age > 43
    4)* weights = 147
1) gender == {female}
5) marital == {single}; criterion = 1, statistic = 49.76
    6)* weights = 207
5) marital == {mar., mar.s, div., wid.}
7)* weights = 360
```

The same function ctree() is used to compute regression trees, where take_job is now a numerical response variable, namely the required income to take a job. According to the regression tree example (section 2.1) the covariates gender, age, nationality and marital status are used as potential splitting covariates.

• Graphical representation of the regression tree

```
> plot(rt_obj)
```

For regression trees the default representation uses box plots to display the distribution of the partitioned response variable in the end nodes.



Figure 3.2: Regression tree: Simulated requested income for taking a job.

Model-based recursive partitioning

• Compute the recursive partitioning of a linear model

```
> mob_obj <- mob(jobvar ~ age + I(age^2) | gender + nation + marital,</pre>
```

> control = mob_control(minsplit = 30), data = dat_job,

```
> model = linearModel)
```

The function mob() is part of the party package as well (Zeileis et al. 2008). The structure of model-based recursive partitioning objects is more complex: Firstly, the model structure is specified. Here, a linear regression model is investigated (see Zeileis et al. 2008, for other specifications). Thus, the linear model explains the dependent variable jobvar through the independent variables age + age² and a u-shaped relationship between the requested income and the predictor variable age is assumed. In R code, the quadratic term for age is generated if $I(age^2)$ is included in the formula (arithmetic operations have a different meaning in the formula context and the interpretation is inhibited using I()). After a vertical bar, potential spitting variables are included, such as gender + nation + marital in the example. Here the control argument is control = mob_control(minsplit = 30, verbose=TRUE), allowing, e.g., to specify minimum splitting node sample sizes or to print test statistics during the computation process via verbose=TRUE.

• Print results from the model-based object

```
> temp <- coef(mob_obj)
> colnames(temp) <- c("Intercept", "age", "age sq.")
> printCoefmat(temp)
Intercept age age sq.
2 998.916 22.613 -0.3640
4 748.667 11.673 -0.1204
5 1229.166 -17.144 0.1808
```

Tables 3.1 and 3.2 in the chapter are generated using the printCoefmat() function to inspect the estimated model parameters in the end nodes. The column names are combined into a vector using c() (starting with c for "concatenate").

• If LATEX is used for text setting, the library **xtable** can be used to generate a latex table (**xtable** has to be installed previous to first usage)

```
> library("xtable")
> print(xtable(temp, align="lrrr", digits=c(0,4,4,4),
> caption="Coefficients of the models in the end nodes.",label="t1"),
> type = "latex", sanitize.text.function = function(x){x})
```

	Intercept	age	age sq.
2	998.9155	22.6134	-0.3640
4	748.6667	11.6731	-0.1204
5	1229.1658	-17.1437	0.1808

Table 3.1: Coefficients of the linear models in the end nodes.

• Plot the model-based recursive partitioning object

>	<pre>plot(mob_obj,</pre>	tp_args =	= list(whic	h = "ag	ge"),	tnex =	2,
>	terminal	_panel = 1	node_bivplo	t(mob_c	obj, w	hich =	"age"))

The specification used here generates a scatter plot in the end nodes with the dependent variable jobtime and the independent variable age on the axes. In the chapter this plot occurs in Figure 3.3.



Figure 3.3: Model-based recursive partitioning: Simulated relationship between age and requested income.

Literature

Dalgaard, P. (2002). Introductory Statistics with R. New York: Springer.

Hothorn, T., Hornik, K., & Zeileis, A. (2006). Unbiased recursive partitioning: A conditional inference framework. *Journal of Computational and Graphical Statistics*, 15, 651–674.

Leisch, F. (2002). Sweave: Dynamic generation of statistical reports using literate data analysis. In W. Härdle & B. Rönz (Eds.), *Compstat 2002 - Proceedings in computational statistics*, Heidelberg: Physica Verlag, (575–580).

R Development Core Team (2009). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.

Zeileis, A., Hothorn, T., & Hornik, K. (2008). Model-based recursive partitioning. *Journal of Computational and Graphical Statistics*, 17, 492–514.