A Framework for
Scorecard Modelling using 

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Short Bio

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1976 — 1997 — 2009 — 2016

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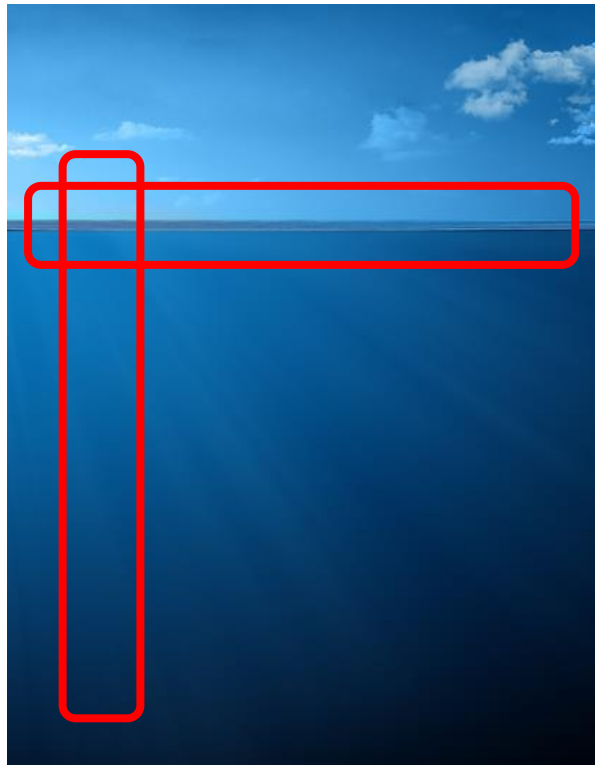
Fraunhofer IDMT

Santander CONSUMER BANK

HOST Hochschule Stralsund

Two years ago… (Bischl, Szepannek and Kühn, 2016)



Typical **business applications** (cf. Szepannek et al., 2017)

- In depth understanding single tasks.
- High degree of business knowledge integration.
- Low degree of automatization.

Typical ML **benchmark studies** focus on

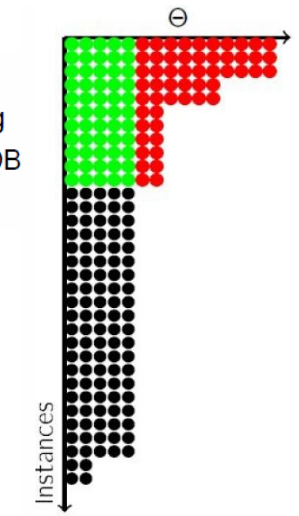
- …testing many algorithms
- …on many data sets
- High degree of automatization.
- Low degree of business understanding.

(…cf. e.g. Baesens et al., 2003, Lessmann et al., 2015, Brown and Mues, 2012, Szepannek et al., 2008, …)

- Class imbalance
- Systematic hyperparameter tuning
- Benchmark experiment on large DB
- Realistic evaluation

mlR

(Szepannek et al., 2010, Bischl et al., 2016)



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Idea of the Project

offers:

…free access to cutting edge methodology from statistics / ML community

Business Requirement

- Integration of expert business knowledge in modelling process
- Proper comparison with existing standards

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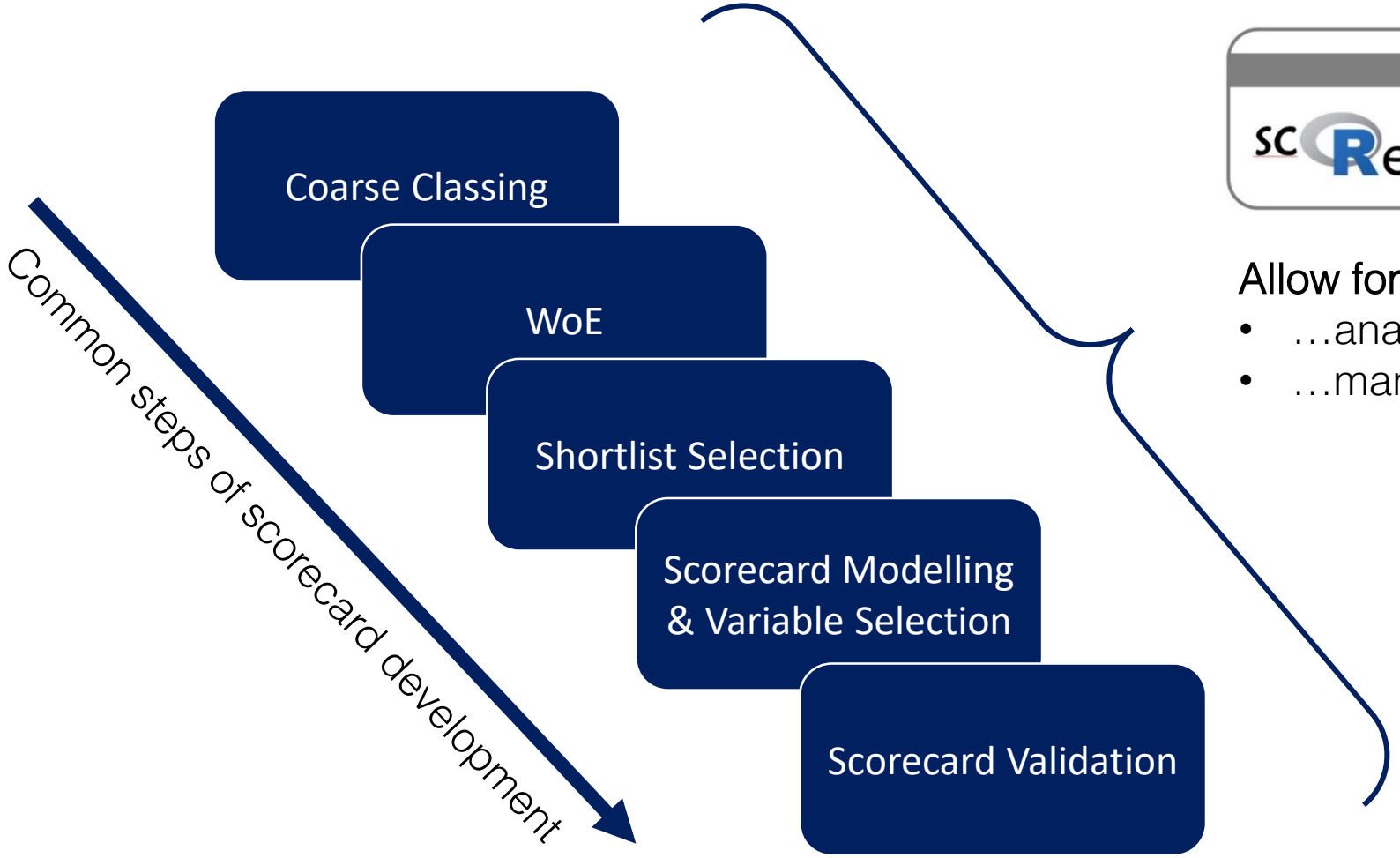
The scoRe Package: Basic Structure



Allow for:

- …analysis & visualization
- …manual interaction

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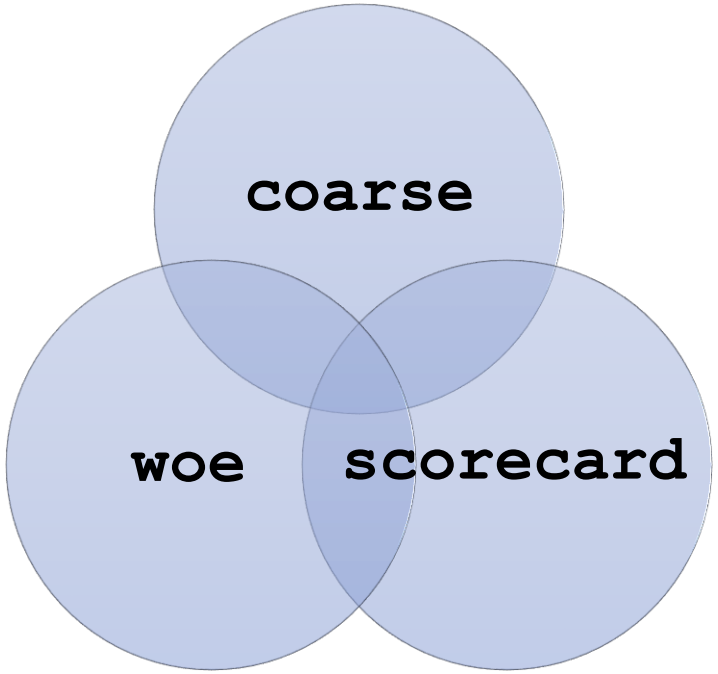
Heart of the Package: 3 Classes

Common misunderstanding:

Preprocessing builds 1st part of the model!



Requirement of proper definition of objects and corresponding `predict()` methods!

…not given by existing implementations.

…several summary and plot methods to allow for an expert analysis & knowledge integration.

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Coarse Classing

- Initial automatic coarse classing as a starting point
  - …by either optimizing IVs
  - …or χ^2 significance tests on differences in BR.
- Output object of class coarse stored.
- …ready for subsequent analysis and expert changements.

coarse {scoRe} R Documentation

Automatic coarse classing

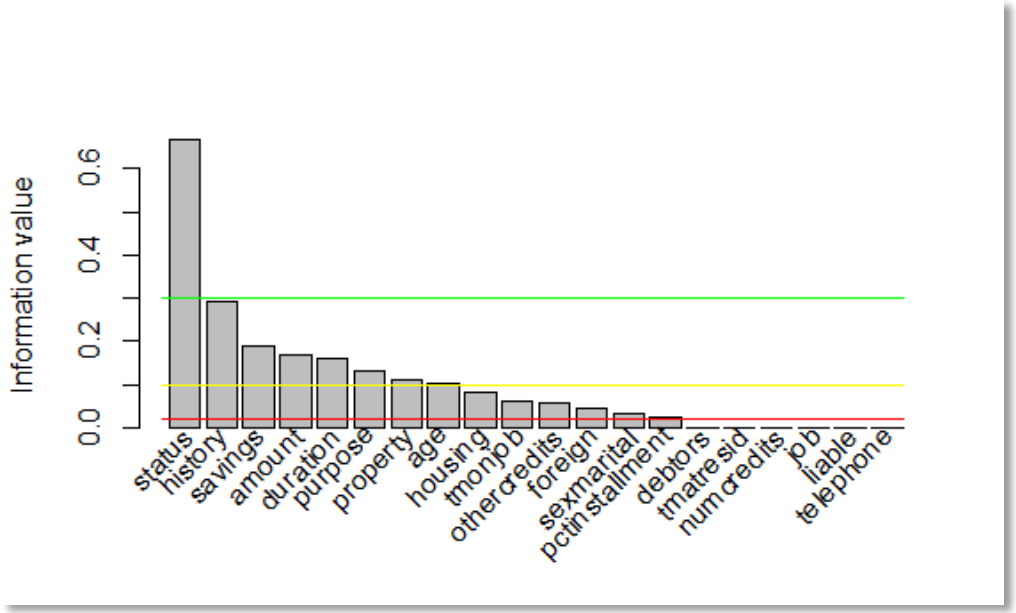
Description

Automatic coarse classing.

Usage

```
coarse(x, ...)

## S3 method for class 'matrix'
coarse(x, y, weights = NULL, pos = "1",
  nom.meth = "chisq", num.meth = "IV", vars = NULL, minsize = 0.05,
  siglev = 0.05, minimp = 0.1, miniv = 0.005, adj = 0.1,
  other = "average")
```



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Analyzing the Binning

Summary of the results:

```
####################################
summary of classing for each variable:
####################################

 status IV: 0.666

          tot good bad  %pop  %def
[-Inf,0)  274  139 135 0.274 0.493
[0,200)   269  164 105 0.269 0.390
[200,Inf)  63   49  14 0.063 0.222
none      394  348  46 0.394 0.117
```

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[200,Inf)  63   49  14 0.063 0.222
none      394  348  46 0.394 0.117
```

Further insights:

```
> res$tmonjob$trace
                lev1       lev2    pvalue merged       br1       br2 size1 size2
1            [0, 1) unemployed 0.7298022   TRUE 0.4069767 0.3709677   172    62
2 [0, 1),unemployed     [1, 4) 0.0310736  FALSE 0.3974359 0.3067847   234   339
3            [1, 4)   [7, Inf) 0.1787006   TRUE 0.3067847 0.2529644   339   253
4   [1, 4),[7, Inf)     [4, 7) 0.1441674   TRUE 0.2837838 0.2241379   592   174
>
> res$tmonjob$desc
                      tot good bad  %pop  %def
[0, 1),unemployed     234  141  93 0.234 0.397
[1, 4),[7, Inf),[4, 7) 766  559 207 0.766 0.270
```

Example of levels with implicit order. Only manual check can indentify inconsistencies here…

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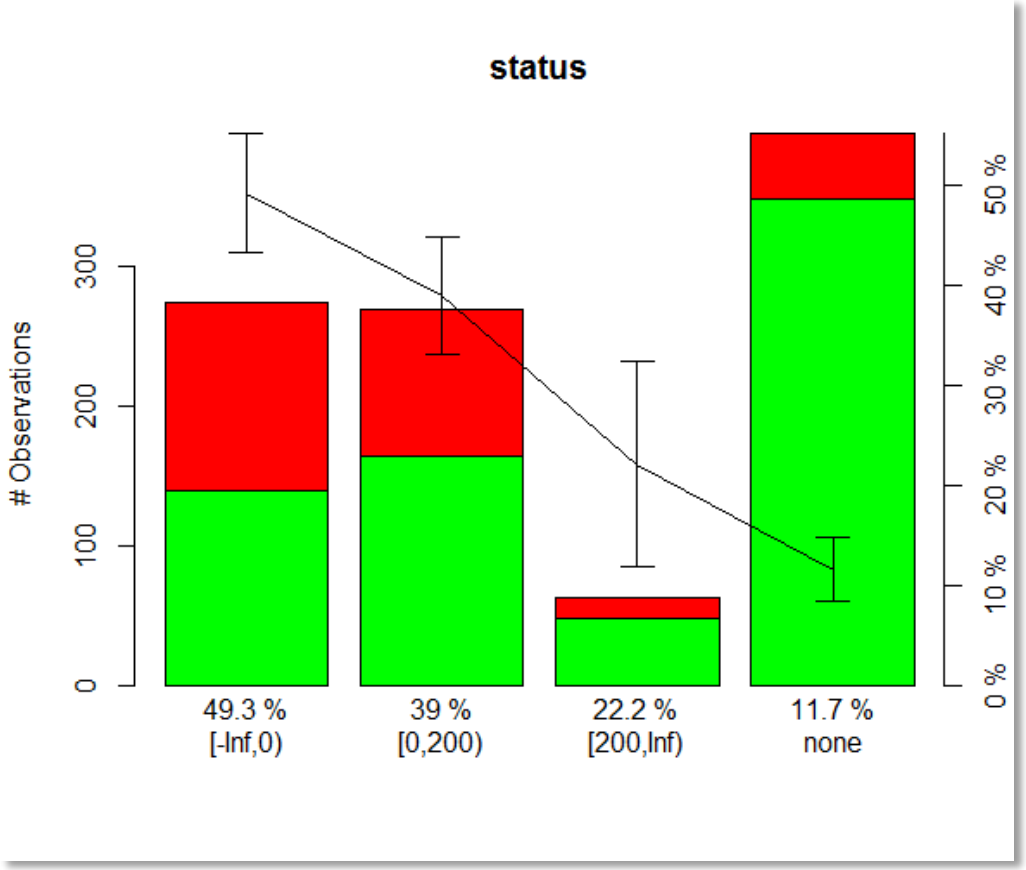
Analyzing and Modifying Binning



Several utilities to manipulate an existing coarse classing model:

- merge
- split
- rename
- autoimpute and
- restore (!).

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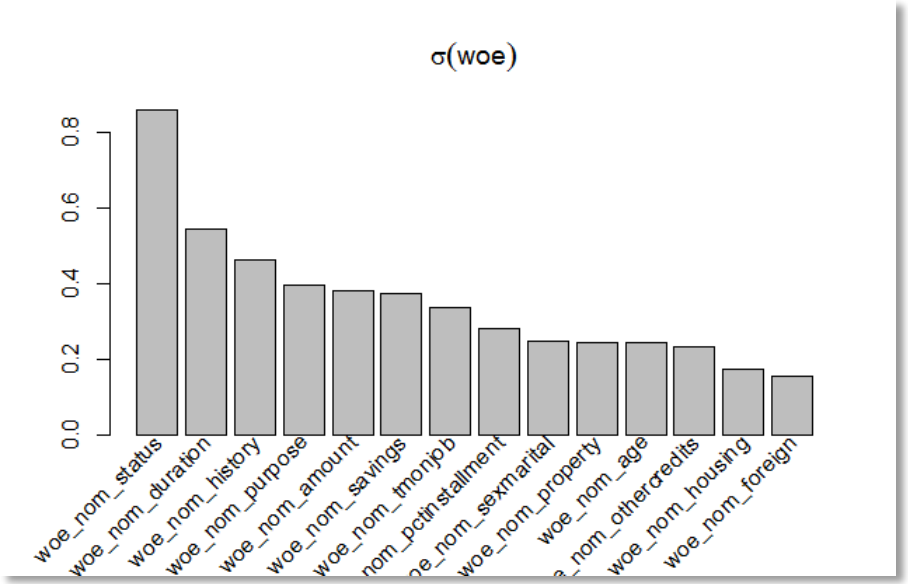
WoEs and Shortlist Selection

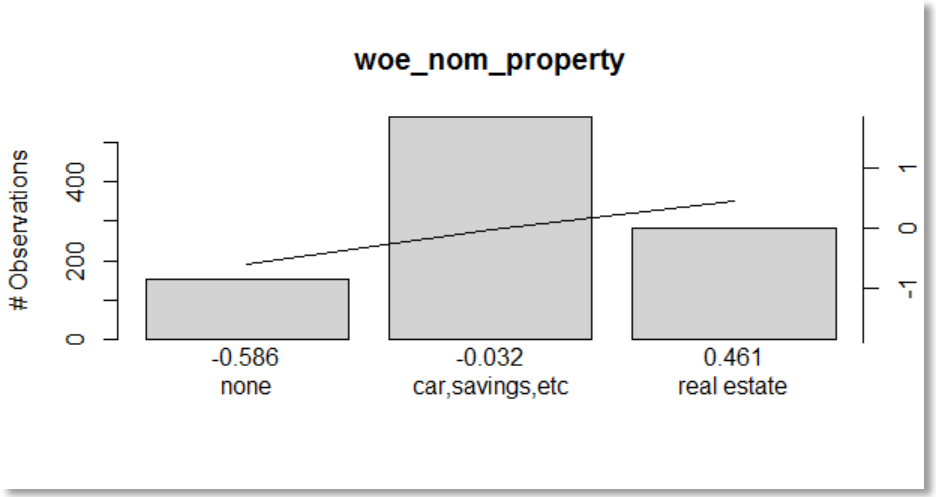
Weights of Evidence:

- It's common practise to use WoEs
  (cf. e.g. Siddiqi, 2006, Finlay 2012, Thomas et al., 2002)
- …stand alone R implementation in Package `klaR` (Roever et al., 2014)
- Implementation similar to coarse.



Short List:

- Preliminary variable exclusions,e.g. by
  - IV
  - PSI
  - Correlations (according to Breiter et al., 2009, Kuhn, 2016)



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Scorecard Objects

- (Still) gold standard: Logistic Regression (→ `glm()` in R, cf. e.g. Sharma, 2008)
- `Scorecard`: conveniance wrapper around glm object.
- Corresponding `predict()` and `plot()` methods.

⇨ all advantages of glm, including variable selection (…e.g. BIC).

- Further: use of continuous characteristics.
- allows for expert analysis (!)
  (several checks implemented)

level	points	pcttot	pctdef	avpd	checks
Total population	NA	1.00	0.3	0.3	OK
(Intercept)	412	NA	NA	NA	OK
woe_nom_status					
none	26	0.394	0.12	0.118	OK
[200,Inf)	9	0.063	0.22	0.209	OK
[-Inf,200)	-14	0.543	0.44	0.443	OK
woe_nom_duration					
(-Inf,33.3]	3	0.83	0.26	0.263	OK
(33.3,43.9]	-9	0.1	0.42	0.409	OK
(43.9, Inf]	-19	0.07	0.57	0.58	OK
woe_nom_history					
critical running	14	0.293	0.17	0.176	OK
positive running,past delays	-2	0.618	0.32	0.314	OK
rest	-24	0.089	0.6	0.608	OK

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Marginal Information

- Alternative VS based on marginal information values (Scallan, 2011)
- Choice between variable candidates → **expert knowledge integration**.
- Tracing the selection process: identifies relevant candidates
- …allows for an easy and intuitive step by step model updating.

```
> autoglm$trace
```

	step 1	step 2	step 3	step 4	step 5	step 6	step 7	step 8
woe_nom_status	0.639	0.000	0.000	0.001	0.000	0.000	0.001	0.001
woe_nom_history	0.292	0.212	0.000	0.000	0.000	0.001	0.001	0.002
woe_nom_amount	0.170	0.139	0.124	-0.001	-0.001	-0.001	0.000	0.001
woe_nom_savings	0.191	0.122	0.122	0.122	-0.001	-0.001	-0.001	-0.002
woe_nom_purpose	0.132	0.097	0.092	0.090	0.087	0.000	0.000	0.000
woe_nom_duration	0.160	0.132	0.114	0.059	0.056	0.061	0.000	0.000
woe_nom_property	0.113	0.096	0.084	0.056	0.056	0.052	0.044	0.000
woe_nom_age	0.062	0.038	0.032	0.035	0.032	0.036	0.036	0.039
woe_nom_foreign	0.044	0.045	0.041	0.038	0.038	0.040	0.039	0.036
woe_nom_sexmarital	0.031	0.023	0.020	0.028	0.028	0.029	0.032	0.034
woe_nom_pctinstallment	0.024	0.024	0.025	0.035	0.037	0.038	0.036	0.034
woe_nom_tmonjob	0.063	0.038	0.034	0.036	0.032	0.030	0.033	0.031
woe_nom_othercredits	0.058	0.049	0.030	0.029	0.030	0.029	0.030	0.027
woe_nom_housing	0.083	0.059	0.049	0.042	0.042	0.041	0.039	0.026

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woe_nom_status          0.639  0.000  0.000  0.001  0.000  0.000  0.001  0.001
woe_nom_history         0.292  0.212  0.000  0.000  0.000  0.001  0.001  0.002
woe_nom_amount          0.170  0.139  0.124 -0.001 -0.001 -0.001  0.000  0.001
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woe_nom_duration        0.160  0.132  0.114  0.059  0.056  0.061  0.000  0.000
woe_nom_property        0.113  0.096  0.084  0.056  0.056  0.052  0.044  0.000
woe_nom_age             0.062  0.038  0.032  0.035  0.032  0.036  0.036  0.039
woe_nom_foreign         0.044  0.045  0.041  0.038  0.038  0.040  0.039  0.036
woe_nom_sexmarital      0.031  0.023  0.020  0.028  0.028  0.029  0.032  0.034
woe_nom_pctinstallment  0.024  0.024  0.025  0.035  0.037  0.038  0.036  0.034
woe_nom_tmonjob         0.063  0.038  0.034  0.036  0.032  0.030  0.033  0.031
woe_nom_othercredits    0.058  0.049  0.030  0.029  0.030  0.029  0.030  0.027
woe_nom_housing         0.083  0.059  0.049  0.042  0.042  0.041  0.039  0.026
```

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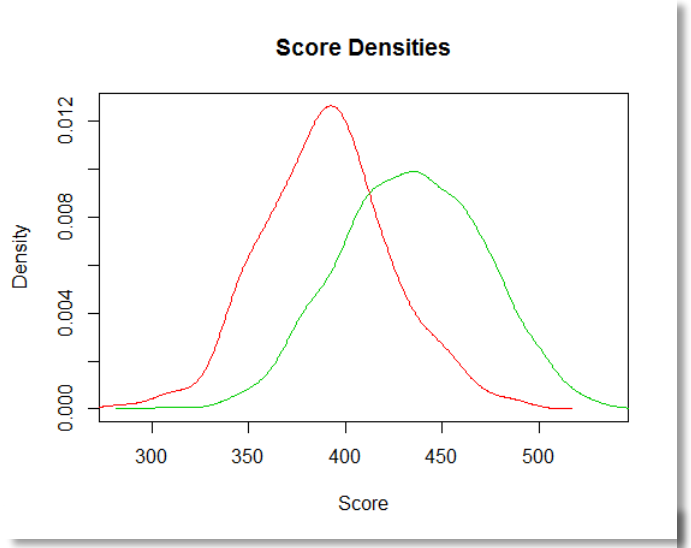
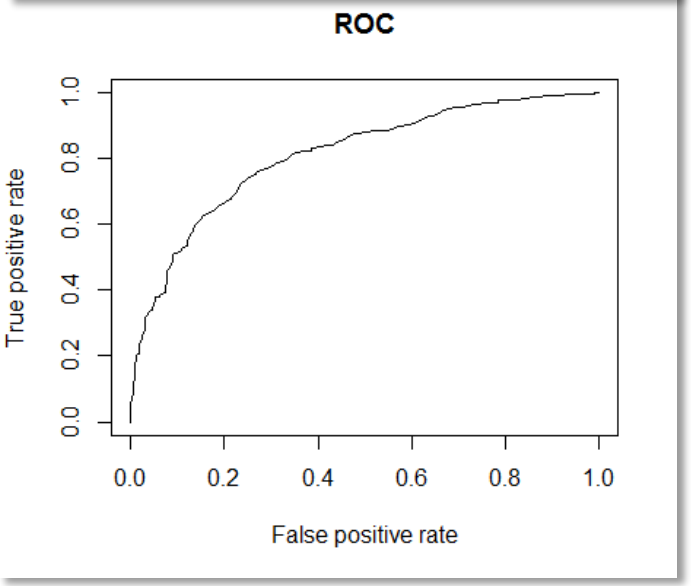
List of Implemented Validation Measures

- Currently 13 different performance measures (not the meaningless standard ones like error rate, precision, …) implemented for both rank ordering and calibration, e.g.:
  - Gini / AUC
  - CLs for the Gini (Henking et al., 2006)
  - KS
  - H-Measure (Hand, 2009)
  - partial AUC (Robin et al., 2011)
  - EMP (Verbraken et al., 2014)
  - Hosmer-Lemeshow test
  - Spiegelhalter test
  - Brier score
  - …
- …reflects observations weights.
- …easily extendable by other R packages.
- Additional wrappers for comparing several measures and models…





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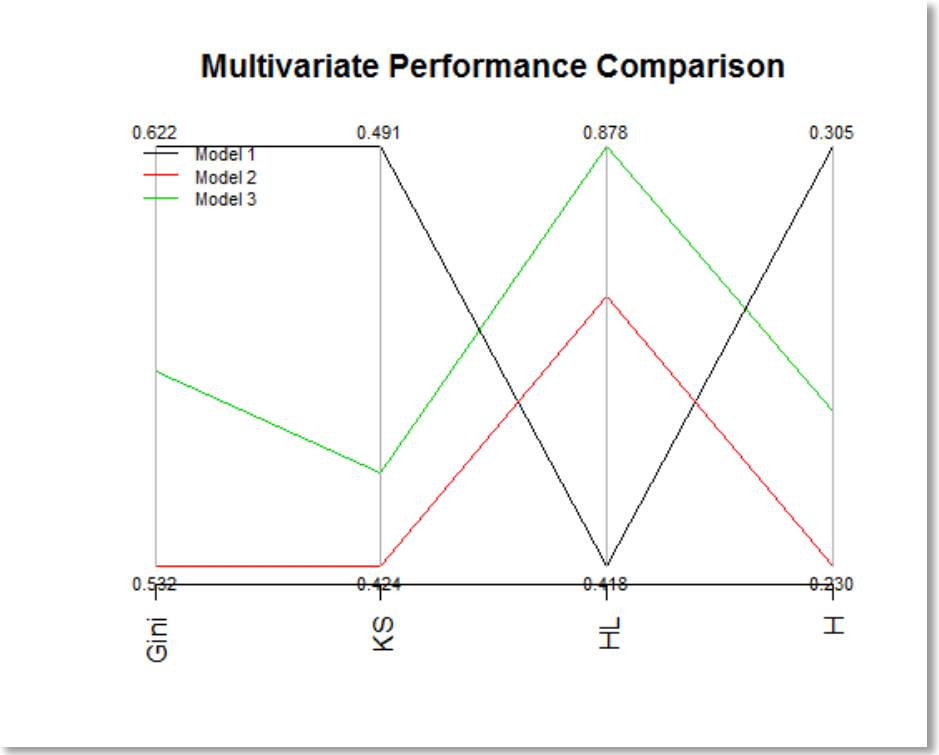
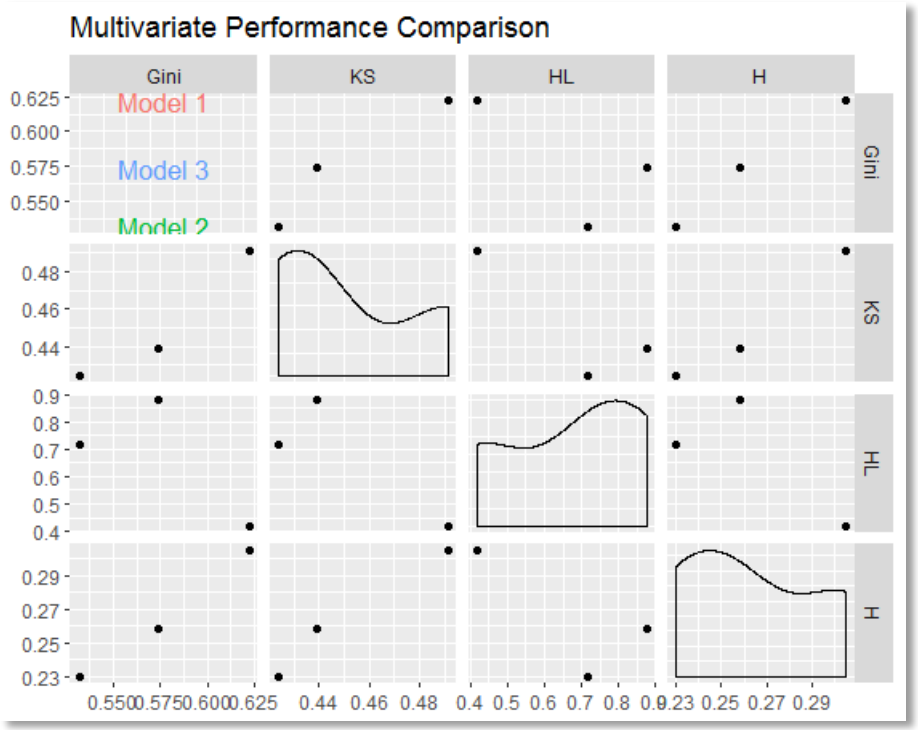
Model Selection

…based on Multivariate Performance Analysis





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Lessons Learned from Existing Shortcomings…

- Proper `predict()` functions.
- Restore option for manual changes of coarse classing.
- Flexibility w.r.t using continuous characteristics in the model.
- Interface to arbitrary classification methods (from other packages), score scalings and validation measures
- Treatment of numerical attributes
- Reflection of weights (typical after RI) (AUC, KS, WoE)
- Properly documented
- …

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…finally some References

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Thank you!

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