Ongoing research towards state-of-the-art in variable and functional form selection for statistical models

Georg Heinze, Aris Perperoglou, Willi Sauerbrei for TG2 of the STRATOS initiative



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Diagnostic and Prognostic Research

COMMENTARY

State of the art in selection of variables and functional forms in multivariable analysis—outstanding issues



Open Access

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Towards recommendations – research required!

- 1. Investigation and comparison of the properties of **variable selection strategies**
- 2. Comparison of spline procedures in univariable and multivariable contexts
- 3. How to model one or more variables with a ,**spike-at-zero**'?
- 4. Comparison of multivariable procedures for model and function selection
- 5. Role of shrinkage to correct for bias introduced by data-dependent modelling
- 6. Evaluation of new approaches for **post-selection inference**
- 7. Adaptation of procedures for **very large sample sizes** needed?



Variable selection: current practice



- Various reviews of model building strategies identified univariate selection still in wide use
- (and its actual, silent use may be even much more widespread)

• TG2 is conducting a review of model building strategies in COVID-19 prediction models



Variable selection – poor guidance?

RESEARCH ARTICLE

Review of guidance papers on regression modeling in statistical series of medical journals

Christine Wallisch^{1,2}*, Paul Bach^{1,3}, Lorena Hafermann¹, Nadja Klein³, Willi Sauerbrei⁴, Ewout W. Steyerberg⁵, Georg Heinze², Geraldine Rauch¹*, on behalf of topic group 2 of the STRATOS initiative¹



Wallisch et al, 2022:

Selection of variables was mentioned in 15 series (65%) and described extensively in ten series (43%) (Fig 5). However, specific variable selection methods were rarely described in detail. *Backward elimination, selection based on background knowledge, forward selection,* and *stepwise selection* were the most frequently described selection methods in seven to eleven series (30–48%). *Univariate screening,* which is still popular in medical research, was only described in three series (13%) in up to one paragraph. Other aspects of variable selection were hardly ever mentioned. *Selection based on AIC/BIC,* relating to best subset selection or stepwise selection based on these information criteria, and the *choice of the significance level* were found in 2 series only (9%). Relative frequencies of aspects mentioned in articles are detailed in Figs 1–3 in <u>S5 File</u>.



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Ongoing work

http://127.0.0.1/5959 Den in Browse

Forward selection, AIC (FSel_AIC)
 Backward elimination, aipha = 0.05 (BE_005)

Backward elimination, AIC (BE AIC)

Full model approximation (FU_approx)

Relaxed Lasso (RLasso)

Adaptive Lasso (AdaLasso)

Select the performance measure

Selection probability (TPR and FPR)

() True/biased/unbiased model selection rate

Calculate measures conditional on selection

Average results over predictors and over noise variables

Lasso

Bias

O RMSE * sqrt(n)

O Power/type-1 error

Local bias of predictions

O Calibration of predictions

O Integrated calibration index

() Local RMSE of predictions

O Global RMSE of predictions

O Coverage

O Cl width

Backward elimination, alpha = 0.50 (BE 05)

Augmented backward elimination, AIC (ABE_AIC)

- Simulation studies:
 - Ullmann (Vienna)
 - Kipruto (Freiburg)
- Education: TG2 workshops at ROeS 2021, Maastricht 2023
- Lectures and workshops by Willi Sauerbrei,
 Frank Harrell,
 Georg Heinze
 & Daniela Dunkler
 and others

Simulation results Simulation design About		
Create plot		Basic scenario: Bias of estimated standardized regression coefficients FU, Full model: Uni_005, Univariate selection with alpha = 0.05; Uni_020, Univariate selection with alpha = 0.20; BE_005, Backward elimination with alpha = 0.05; BE_AIC, Backward elimination with al
basic	-	Predictors are represented by solid lines, and noise variables by dashed lines. The stronger the effect of a predictor, the thicker the line. The higher the multiple R ² of a predictor or noise variable, the more reddish the line.
		For predictors, bias>0 denotes bias away from 0 and bias<0 denotes bias towards 0.
Select methods to compare		-
Full model (FU)		Mittiple correlation
Univariate selection, alpha = 0.05 (Uni_005)		iow righ – – – Nose vanable – Predictor
Invariate selection alpha = 0.20 (101, 020)		

Visualization of simulation results: Comparison of variable selection methods





Key messages about variable selection

- Purpose of model? Descriptive, explanatory, or predictive?
 - Effects on MSE of coefficient estimates
 - Effects on prediction error
- \rightarrow Relative performance of methods depends on sample size
- The true ,model' is rarely identified
- Inference is wrong where does it matter?
- Accept model uncertainty as another source of variation



The role of background knowledge Some STRATOS-triggered cooperations (project SAMBA)

- Good examples for background knowledge: Nottingham Prognostic Index (Breast Cancer) Framingham risk score (Cardiovascular Med.)
- But: Poorly conducted studies generate background "knowledge" that is of little use
- Does RF prediction improve by making use of selection results from previous studies?



BMC Medical Research Methodology

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RESEARCH

Statistical model building: Background "knowledge" based on inappropriate preselection causes misspecification

Lorena Hafermann^{1*}, Heiko Becher², Carolin Herrmann¹, Nadja Klein³, Georg Heinze⁴ and Geraldine Rauch¹



Article

Using Background Knowledge from Preceding Studies for Building a Random Forest Prediction Model: A Plasmode Simulation Study

Lorena Hafermann¹, Nadja Klein^{2,*}, Geraldine Rauch¹, Michael Kammer³ and Georg Heinze^{3,*}

Functional form selection: Spline procedures

REVIEW

A review of spline function procedures in R

Aris Perperoglou^{1*}, Willi Sauerbrei², Michal Abrahamowicz³, Matthias Schmid⁴ on behalf of TG2 of the STRATOS initiative



Perperoglou et al. BMC Medical Research Methodology (2019) 19:46 https://doi.org/10.1186/s12874-019-0666-3 BMC Medical Research Methodology

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Check for updates



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Spline procedures: current questions

• Which estimator is the ,best'?



Performance Measure Selector

Target:	Type of summation:
 Functional form 	 Expectation
Predictions	Expectation over dF(X)
 Effect estimate of Intervention 	 Expectation over precision of reference function
l ocalisation:	O Maximum
Global	O Minimum
 Local 	⊖ Median
Loss:	
 Difference 	
O Absolute	
Squared	
Epsilon-level accuracy	
Dimension:	
• Y	
⊖ x	

→Many different performance measures can be, designed' by combining different aspects

 \rightarrow Which of them are suitable?

Currently: evaluation of performance measures Next step: comparison of splines

Combining variable and functional form selection

• Several, philosophies':

	Multivariable fractional polynomials (mfp2)	Restricted cubic splines (rms)	Penalized/thin plate splines (mgcv)
Selection	Significance-based	No	Penalty-based
Smoothing	Global: x^{p_1}, x^{p_2}	Local: spline based	Local: spline based
Basis functions (4df)	2 per variable (FP2)	4 per variable	,many' per variable









Comparison in Pima data set:

- Predicting diabetes onset (yes/no) in 768 members of Pima nation
- 8 cont. predictors 4 selected (6 df) (8 included, 32 df) 6 selected (11.2 edf) • MMM • Partial linear ₩ 0-**₩** 0-**≝** 0predictors for BMI: -4 · -4 --4 -3.9 edf 4 df 4 df MEDICAL UNIVERSITY 30 30 20 50 20 40 50 60 30 40 60 20 40 50 60 VIENNA BMI BMI BMI

Role of shrinkage

STUDY PROTOCOL

Comparison of variable selection procedures and investigation of the role of shrinkage in linear regression-protocol of a simulation study in low-dimensional data

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A. Variable selection methods

Method	Tuning parameters	Initial estimates
Lasso	10-fold CV, AIC & BIC	N/A
Garrote	10-fold CV, AIC & BIC	OLS, ridge and lasso
Alasso*	10-fold CV, AIC & BIC	OLS, ridge and lasso
Rlasso*	10-fold CV, AIC & BIC	N/A
Best subset	10-fold CV, AIC & BIC	N/A
BE*	10-fold CV, AIC & BIC	N/A

B. Post-estimation shrinkage methods:

(i) Global [10], (ii) parameterwise [9] and (iii) Breiman's method [5] Estimation method: (i) leave-one-out CV and (ii) 10-fold CV

PlosOne 2022

Talk by Edwin Kipruto @CEN 2023



Evaluation of selective inference STRATOS-triggered cooperation

- What is ,selective inference'?
 - Sub-model inference:
 Inference after selection'
 - Taking selected model as a new given
 - New methods

Kammer et al. BMC Medical Research Methodology (2022) 22:206 https://doi.org/10.1186/s12874-022-01681-y BMC Medical Research Methodology

RESEARCH



Evaluating methods for Lasso selective inference in biomedical research: a comparative simulation study

Michael Kammer^{1,2}, Daniela Dunkler¹, Stefan Michiels³ and Georg Heinze^{1*}

- ,Full model' inference:
 - Selection sets some $\beta = 0$
 - Inference targets

 full model
 (also non-'selected' variables)

Conclusions: Despite violating nominal coverage levels in some scenarios, selective inference conditional on the Lasso selection is our recommended approach for most cases. If simplicity is strongly favoured over efficiency, then sample splitting is an alternative. If only few predictors undergo variable selection (i.e. up to 5) or the avoidance of false positive claims of significance is a concern, then the conservative approach of PoSI may be useful. For the adaptive Lasso, SI should be avoided and only PoSI and sample splitting are recommended. In summary, we find selective inference useful to assess the uncertainties in the importance of individual selected predictors for future applications.



Adaptation for big data sets

- Big data sets (many observations) make any p-values ridiculously small
- How to separate relevant from irrelevant effects?
- Model size depends on purpose of the model
 - Should the model be communicable or a ,black-box'?
 - Can the model be applied electronically (e.g. on EHRs)?
 - Model approximation/projection?
- Ongoing project in the context of MFP (Willi Sauerbrei, Patrick Royston, Aris Perperoglou)



STRATOS cooperations between TGs

• TG2-TG4: effects of measurement error on functional form estimation See talk by Aris Perperoglou and Michal Abrahamowicz

- TG2-TG3: ,Regression without regrets'
 - Initial data analysis before regression analysis
 - Paper to be submitted soon; previous talks at ISCB 2020, IBC 2022



Simulation studies – key instruments to compare approaches

Boulesteix et al, Significance 2020

There is a clear need for more neutral comparisons and replications of methodological statistical research, but how should such studies be performed? Surprisingly, the design of comparison studies of statistical methods has hardly been addressed



Pawel et al, BiomJ 2023:

We show how easy it is to make the method appear superior over well-established competitor methods if no protocol is in place and various questionable research practices are employed



Heinze, Boulesteix, Kammer, Morris, White (STRATOS Simulation Panel), *BiomJ* 2023: Biostatistical methods are typically developed and evaluated in **four phases**; only after **Phase IV** we know when a method **is or is not the preferred method** Each phase needs different type of simulation study

 Special issue in Biometrical Journal devoted to 'Neutral Comparison Studies' (to be released very soon)



Conclusion

- In many areas, we have enough methods but we don't know yet which one to recommend/discourage from
- We need evidence generated in neutral comparison studies of Phases III and IV:
 - Simulation studies
 - Comparative studies based on example data sets
- Which methods can we generally recommend?
 - To level-1 data analysts?
 - To level-2 statisticians?





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