Marcel Dettling

Institute for Data Analysis and Process Design

Zurich University of Applied Sciences

marcel.dettling@zhaw.ch

http://stat.ethz.ch/~dettling

ETH Zürich, November 26, 2012

Cross Validation: Why?

- On a given dataset, a *bigger model* always yields a *better fit*, i.e. smaller residuals, and thus better RSS, R-squared, error variance, etc.
- Bigger models have an *unfair advantage* because there are *more predictors*. AIC/BIC and the F test try to balance this by penalizing for the number of predictors used.
- If the *ultimate goal* is *predicting new datapoints*, then it is self suggesting to identify a model which does well at this. For making the right choice, we mimic the prediction task on our training sample with *Cross Validation*. This is also the only option for testing the performance of variable transformations.

10-Fold Cross Validation

Idea:

- 0) Split the (training) data into 10 equally sized folds.
- 1a) Use folds **1-9** for the *fit*, and use the model to *predict* fold **10**.
- 1b) On fold **10**, the forecasting performance is measured by computing the RSS, i.e. the *squared difference* between the *forecasted and true values*.
- 2) Use folds **1-8 & 10** for *fitting*, predict fold **9** and *record RSS*.
- 3) Use folds 1-7 & 9-10 for *fitting*, predict fold 8 and *record RSS*4) ...

10-Fold Cross Validation

Summary:

- Each observation is forecasted and compared against the true value exactly 1x. On the other hand, it is used 9x during the model fitting process.
- With cross validation, we evaluate the "out-of-sample" performance, i.e. how precisely a model can forecast observations that were not used for fitting the model.
- In this regard, bigger and/or more complex models are not necessarily better than smaller/simpler ones.

Cross Validation

Further remarks:

- Cross validation is often used for identifying the most predictive model from a few candidate models that were found by stepwise variable selection procedures.
- There are alternatives to 10-fold CV. Popular is n-fold CV, which is known as Leave-One-Out Cross Validation.
- In R, it's easy to code "for-loops" that do the job, but there are also existing functions (that have some limits...):
 - > library(DAAG)
 - > CVlm(data, formula, fold.number, ...)

Cross Validation

Using for() to program cross validation loops:

```
> rss <- c()
> fo <- 10
> sb <- round(seq(0,nrow(dat),length=(fo+1)))</pre>
> for (i in 1:folds)
 {
>
   test <- (sb[((fo+1)-i)]+1):(sb[((fo+2)-i)])
>
 train <- (1:nrow(dat))[-test]</pre>
>
 fit <- lm(res ~ p1+..., data=dat[train,])</pre>
>
 pred <- predict(fit, newdata=dat[test,])</pre>
>
 rss[i] <- sum((dat$response[test] - pred)^2)
>
> }
```

Modeling Strategies

 In which order to apply: estimation – diagnostics – transformation – variable selection???

There is no definite answer to this: regression analysis is the search for structure in the data and there are no hard-and-fast rules about how it should be done.

Professional regression analysis can be seen as an art and definitely requires skill an expertise – one must be alert to unexpected structure in the data.

 \rightarrow We here provide a rough guideline for regression analysis

Guideline for Regression Analysis

0) Preprocessing the data

- learning the meaning of all variables
- give short and informative names
- check for impossible values, errors
- if they exist: set them to NA
- systematic or random missings?

1) First-aid transformations

- bring all variables to a suitable scale
- use statistical and specific knowledge
- routinely apply the first-aid transformations

Guideline for Regression Analysis

- 2) Fitting a big model
 - First fit a big model with potentially too many predictors
 - use all if p < n/5
 - preselect manually according to previous knowledge
 - preselect with forward search and a p-value of 0.2

3) Model Diagnostics

Check for normality, constant variance, uncorrelated errors:

- transformations
- robust regression
- weighted regression
- dealing with correlation

Guideline for Regression Analysis

6) Interactions

- try (two-way) interactions
- do only use predictors that are in the model

7) Influential data points

- attractors for the regression line
- keep them or skip them?
- compare with and without

8) Do model and coefficients make sense?

- implausible predictors, wrong signs, against theory, ...
- remove if there are no drastic changes!

Guideline for Regression Analysis

If there were substantial changes to the model in steps 4-8), then one should go back to 3) and repeat the diagnostics.

Hypothesis testing:

- proceed similarly
- careful: transformations, selection, collinearity
- question dictates what works and what not!

Prediction:

- guideline is still reasonable
- we are a little less picky here in selection and diagnostics
- check generalization error with test data / cross validation

Significance vs. Relevance

The larger a sample, the smaller the p-values for the very same predictor effect. Thus do not confuse a small p-values with an important predictor effect!!!

With large datasets:

- statistically significant results which are practically useless
- we have high evidence that a blood value is lowered by 0.1%

Models are approximative:

- most predictors have influence, thus $\beta_i = 0$ never holds
- point null hypothesis is usually wrong in practice
- we just need enough data to be able to reject it

Significance vs. Relevance

Absence of Evidence \neq Evidence of Absence

- if one fails to reject a null hypothesis $\beta_j = 0$ we do not have a proof that the predictor does not influence the response.
- things may change if we have more data, or even if the data remain the same, but the set of predictors is altered.

Measuring the Relevance of Predictors:

- maximum effect of a predictor variable on the response: $\beta_j \cdot (\max_i x_{ij} - \min_i x_{ij})$
- this can be compared to the total span in the reponse, or it can be plotted vs. the (logarithmic) p-value.

Mortality: Which Predictors Are Relevant?

> summary(fit.step)

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	1031.9491	80.2930	12.852	< 2e-16	* * *
JanTemp	-2.0235	0.5145	-3.933	0.00025	* * *
Rain	1.8117	0.5305	3.415	0.00125	* *
Educ	-10.7463	7.0797	-1.518	0.13510	
NonWhite	4.0401	0.6216	6.500	3.1e-08	* * *
WhiteCollar	-1.4514	1.0451	-1.389	0.17082	
log.NOx	19.2481	4.5220	4.257	8.7e-05	* * *

Residual standard error: 33.72 on 52 degrees of freedom Multiple R-squared: 0.7383, Adjusted R-squared: 0.7081 F-statistic: 24.45 on 6 and 52 DF, p-value: 1.543e-13

Mortality: Which Predictors Are Relevant?

Implementing the idea of maximum predictor effect:

>	mami	<- function(col) max(col)-min(col)						
>	ranges	<- apply(mort,2,mami)[c(2,5,6,8,9,14)]						
>	ranges							
Ja	anTemp	Rain	Educ	NonWhite	WhiteCollar	log.NOx		
	55.00	55.00	3.30	37.70	28.40	5.77		
>								
>	rele	<- abs(ranges*coef(fit.step)[-1])						
>	rele							
Ja	anTemp	Rain	Educ	NonWhite	WhiteCollar	log.NOx		
-	L11.29	99.64	35.46	152.31	41.22	110.97		

Predictor contributions are quite evenly distributed here. Maximum span in the response is **322.43**

Final Remarks to Multiple Linear Regression

All models we fit are most likely too simple/wrong...

However, some of these turn out to be really useful...

And some are more, and other are less useful...

Identifying the "good" ones is your job!