

The R Package regtools and the Mystery of P-Values

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These slides at <http://heather.cs.ucdavis.edu/Iowa.pdf>

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- Introduction to my R package **regtools**, especially in terms of regression diagnostics.
- Comments on the dramatic recent ASA announcement regarding p-values.

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- Meant to accompany my forthcoming book, *From Linear Models to Machine Learning: Regression and Classification, with R Examples*.
- In many senses, both the package and the book *take a very nontraditional point of view*.

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The Book

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- Interweaves nonparametric methods with linear and nonlinear parametric regression models.

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- As with the book, interweaves nonparametric methods with linear and nonlinear parametric regression models.
- Includes some unusual functions, both in the sense of new ways of doing old things, and ways of doing new things.
- Work in progress, adding more functions over time.

Example: Multiclass Classification

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```
> trnidxs ← sample(1:310,225)
> predidxs ← setdiff(1:310,trnidxs)
> ovout ← ovalogtrn(3,vert[trnidxs,])
> predy ← ovalogpred(ovout,vert[predidxs,1:6])
> mean(predy == vert[predidxs,7])
[1] 0.8823529
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Similar success rates, but AVA much more computation.

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```
> data(ltrfreqs)
> ltrfreqs ← ltrfreqs[order(ltrfreqs[,1]),]
> truepriors ← ltrfreqs[,2]/100 # not Bayesian!
# success rate with sample priors 0.75
> trnout1 ← ovakntrn(lrtrn[,1], xdata, 26, 50,
                    truepriors)
> ypred ← ovaknpred(trnout1, lrtest1[, -1])
> mean(ypred == lrtest1[, 1])
[1] 0.8787988 # nice!
```

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Model Fit Assessment

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- Classical approach: Plot residuals.

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- NM book/**regtools** approach: Use the nonparametric to help assess the parametric.

Example: Currency Data (Fong & Ouliaris, 1995)

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- Predict *yen* from Can. \$, *mark*, *franc*, *pound*.

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- Predict *yen* from Can. \$, *mark*, *franc*, *pound*.
- Linear model:

```
> fout <- lm(Yen ~ ., data=cur1)
> summary(fout)
```

```
...
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	102.855	14.663	7.015	5.12e-12
Can	-45.941	11.979	-3.835	0.000136
Mark	147.328	3.325	44.313	< 2e-16
Franc	-21.790	1.463	-14.893	< 2e-16
Pound	-48.771	14.553	-3.351	0.000844

```
...
```

```
Mult. R-squared: 0.8923, Adj. R-squared: 0.8918
```

Currency Data, contd.

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- Nonparametric fit: k-NN, k det. by cross-val:

```
> xdata ← preprocessx(curr1[, -5], 150, xval=TRUE)
> kminout ← kmin(curr1$Yen, xdata, predwrong, nk=30)
> kminout$kmin
[1] 5
> kout ← knnest(curr1[, 5], xdata, 5)
> cor(kout$regest, curr1[, 5])^2
[1] 0.9920137
```

Currency Data, contd.

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We're “leaving money on the table”!

Currency

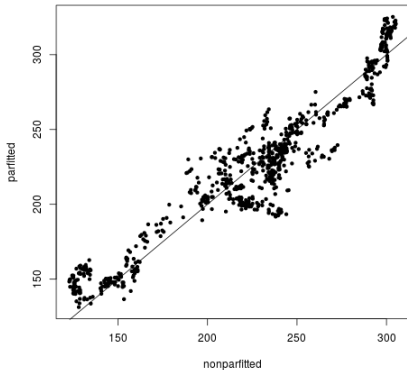
Currency

Plot parametric vs. nonparametric fits:

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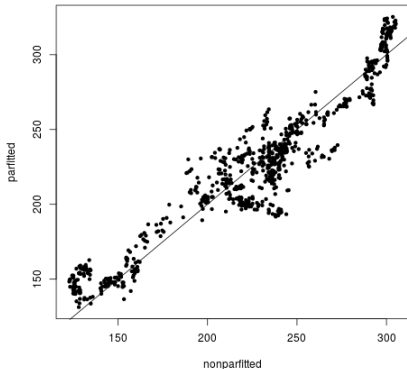
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> parvsnonparplot(fout1, kout)
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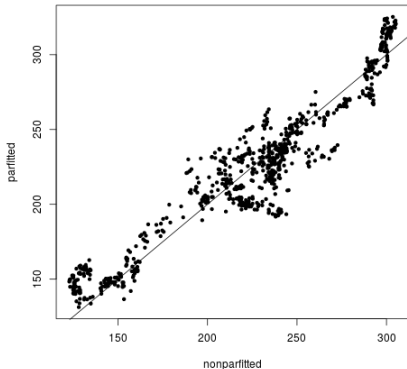


Interesting features, especially “hook” at the left end and “tail” near the middle.

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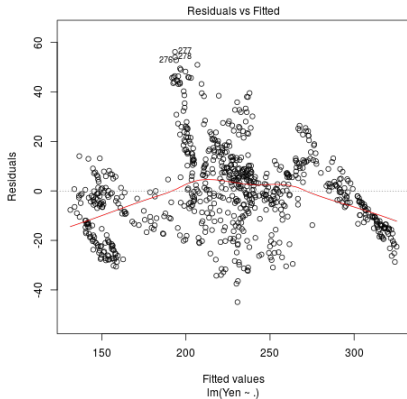
Interesting features, especially “hook” at the left end and “tail” near the middle. Bring in the domain experts!

Currency

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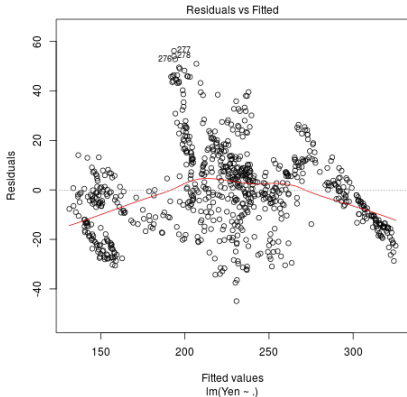
R built-in plot:

```
> plot(lmout)
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Hook, tail visible here too, but arguably less clearly.

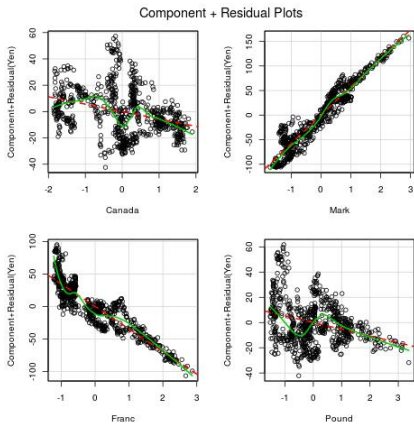
Currency

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Draw partial residual plots, using the `car` package.

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> crPlots(fout1)
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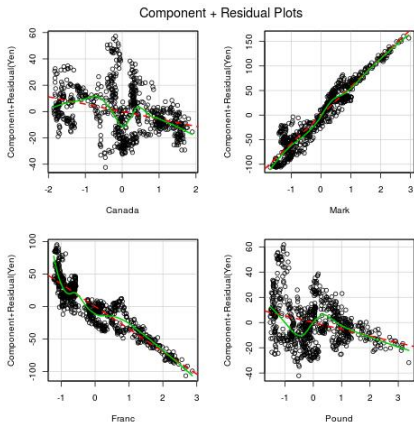


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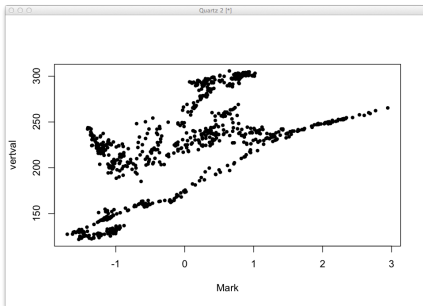
Mark plot looks rather “clean.” And yet...

Currency

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Drawing a similar plot from **regtools**, which uses smoothing:

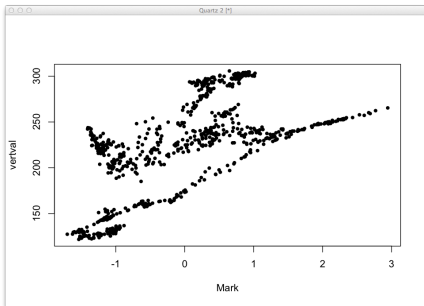
```
> nonparvsxplot(kout)
next plot
next plot
next plot
next plot
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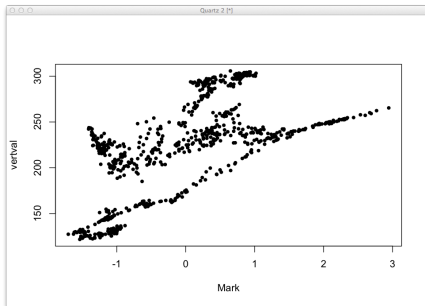
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Not so clean at all!

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Not so clean at all! Again, need domain experts.

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- Fortunately, ASA decided to address the issue recently.
- The report is “a camel designed by a committee,” thus not as strong as it should be. But at the very least, one can say that the report is very negative about typical usage today of p-values.

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Example: MovieLens data.

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```
> head(uu)
  userid age gender      occup   zip  avg_rat
1      1  24      0 technician 85711 3.610294
2      2  53      0      other 94043 3.709677
> q ← lm(avgrat ~ age + gender, data=uu)
> summary(q)
...
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.4725821  0.0482655  71.947 < 2e-16 **
age           0.0033891  0.0011860   2.858  0.00436 **
gender       0.0002862  0.0318670   0.009  0.99284
...
Multiple R-squared:  0.008615,  Adjusted R-squared:
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Age effect is “highly significant” — yet **highly unimportant**.

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- Stat instructors like telling “favorite bedtime stories” to their kids, and **don’t want to change**
- Will the ASA statement have any effect????