

432 Class 12 Slides

github.com/THOMASELOVE/432-2018

2018-02-22

Setup

```
library(skimr)
library(pROC)
library(ROCR)
library(rms) # note: also loads Hmisc
library(simputation)
library(broom)
library(tidyverse)
```

Today's Materials

- Logistic Regression and the Framingham Study (conclusion)
- Performing Linear Regression with `ols`
- Hormone Therapy and Baseline LDL in the HERS trial

The HERS trial is described in Vittinghoff et al., especially Chapter 4.

Logistic Regression and Framingham

Data Ingest, Cleanup (from Class 10)

```
fram <- read.csv("data/fram_new.csv") %>% tbl_df
set.seed(432001)
fram1 <- fram %>%
  impute_pmm(educ + cigs_day + heart_r ~ age + smoker) %>%
  impute_rlm(bmi + tot_chol ~ sex + age + sbp + heart_r) %>%
  impute_pmm(bp_meds ~ hx_htn + bmi + tot_chol) %>%
  impute_rlm(glucose ~ hx_dm + bmi + tot_chol + age) %>%
  mutate(ed_f = fct_recode(factor(educ),
    "1_Some_HS" = "1", "2_HS_grad" = "2",
    "3_Some_Col" = "3", "4_Col_grad" = "4"))
fram2 <- fram1 %>%
  select(subj, sex, age, smoker, cigs_day, bp_meds,
    hx_stroke, hx_htn, hx_dm, ed_f, tot_chol,
    sbp, dbp, bmi, heart_r, glucose, CHD_10)
```

The Models We've Fit (predicting CHD_10)

```
m_01 <- glm(CHD_10 ~ hx_htn, data = fram2,
            family = binomial)

d <- datadist(fram2)
options(datadist = "d")
m_01_lrm <- lrm(CHD_10 ~ hx_htn, data = fram2, x = T, y = T)

m_02 <- glm(CHD_10 ~ hx_htn + tot_chol,
            data = fram2, family = binomial)
m_02_lrm <- lrm(CHD_10 ~ hx_htn + tot_chol, data = fram2,
               x = TRUE, y = TRUE)
```

Then We Fit a Kitchen Sink Model (Class 11)

```
m_03 <- glm(CHD_10 ~ hx_htn + tot_chol + sex + age +  
             smoker + cigs_day + bp_meds +  
             hx_stroke + hx_dm + ed_f + sbp + dbp +  
             bmi + heart_r + glucose,  
            data = fram2, family = binomial)  
  
d <- datadist(fram2)  
options(datadist = "d")  
m_03_lrm <- lrm(CHD_10 ~ hx_htn + tot_chol + sex + age +  
               smoker + cigs_day + bp_meds +  
               hx_stroke + hx_dm + ed_f + sbp + dbp +  
               bmi + heart_r + glucose,  
              data = fram2, x = TRUE, y = TRUE)
```

Comparing the Current Models

Model	C statistic	Nagelkerke R^2
m_01_1rm	0.614	0.051
m_02_1rm	0.640	0.055
m_03_1rm	0.733	0.159

m_03_1rm shows the following predictors as highly significant:

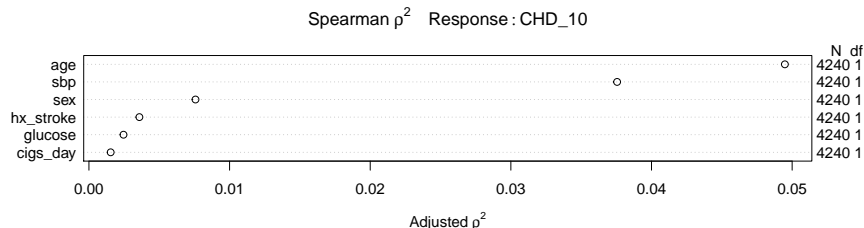
- age, sex, sbp, cigs_day, glucose, and hx_stroke

Fitting a 6-predictor, but still useful model

What looks useful?

By ANOVA on `m_03_1rm` it looks like `age`, `sex`, `sbp`, `cigs_day`, `glucose`, `hx_stroke` for sure.

```
plot(spearman2(CHD_10 ~ age + sex + sbp + cigs_day +  
              glucose + hx_stroke, data = fram2))
```



New Model 4

```
m_04 <- glm(CHD_10 ~ rcs(age, 5) + rcs(sbp, 3) + sex +  
            hx_stroke + glucose + cigs_day,  
            data = fram2, family = binomial)  
  
dd <- datadist(fram2)  
options(datadist = "dd")  
  
m_04_lrm <- lrm(CHD_10 ~ rcs(age, 5) + rcs(sbp, 3) + sex +  
               hx_stroke + glucose + cigs_day,  
               data = fram2, x = TRUE, y = TRUE)
```

m_04_lrm

```
> m_04_lrm
```

```
Logistic Regression Model
```

```
lrm(formula = CHD_10 ~ rcs(age, 5) + rcs(sbp, 3) + sex + hx_stroke +  
      glucose + cigs_day, data = fram2, x = TRUE, y = TRUE)
```

		Model Likelihood Ratio Test		Discrimination Indexes		Rank Discrim. Indexes	
Obs	4240	LR chi2	401.44	R2	0.158	C	0.731
0	3596	d.f.	10	g	1.041	Dxy	0.461
1	644	Pr(> chi2)	<0.0001	gr	2.833	gamma	0.461
max deriv	2e-06			gp	0.120	tau-a	0.119
				Brier	0.115		

	Coef	S.E.	Wald Z	Pr(> Z)
Intercept	-8.7201	2.4092	-3.62	0.0003
age	0.0732	0.0576	1.27	0.2037
age'	0.2871	0.3539	0.81	0.4172
age''	-1.1057	0.9608	-1.15	0.2498
age'''	1.4723	0.9640	1.53	0.1267
sbp	0.0147	0.0066	2.23	0.0256
sbp'	0.0030	0.0080	0.37	0.7080
sex=M	0.4935	0.0973	5.07	<0.0001
hx_stroke	1.0514	0.4345	2.42	0.0155
glucose	0.0076	0.0016	4.69	<0.0001
cigs_day	0.0208	0.0039	5.39	<0.0001

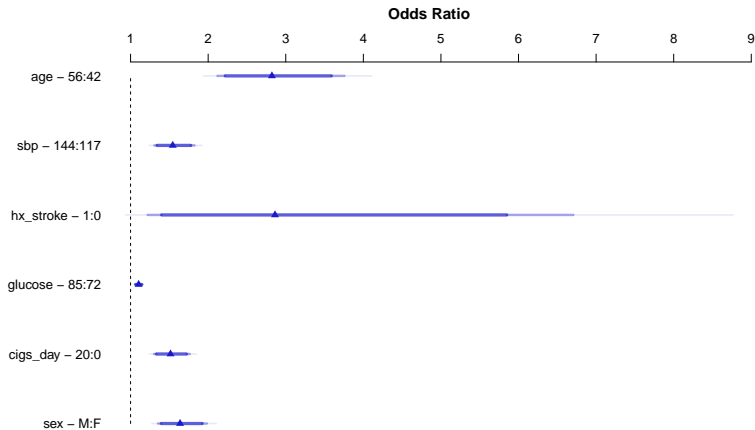
Validating our Summary Statistics

```
set.seed(432329); validate(m_04_lrm)[1:4,]
```

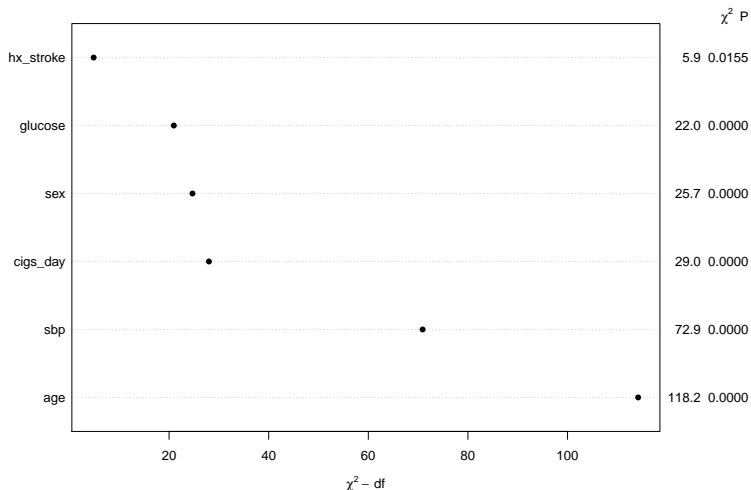
	index.orig	training	test	optimism
Dxy	0.4611110	0.4672261	0.45678154	0.010444568
R2	0.1575417	0.1629811	0.15375377	0.009227324
Intercept	0.0000000	0.0000000	-0.04796015	0.047960154
Slope	1.0000000	1.0000000	0.96803833	0.031961665

	index.corrected	n
Dxy	0.45066647	40
R2	0.14831438	40
Intercept	-0.04796015	40
Slope	0.96803833	40

```
plot(summary(m_04_lrm))
```

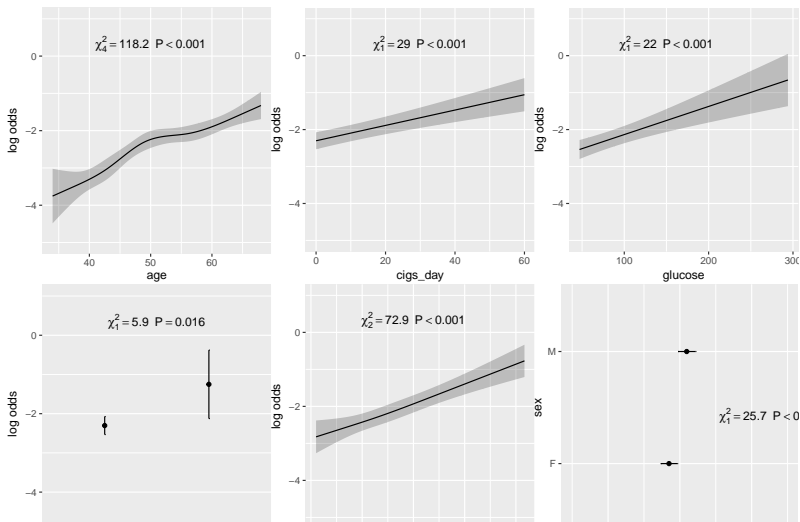


```
plot(anova(m_04_lrm))
```



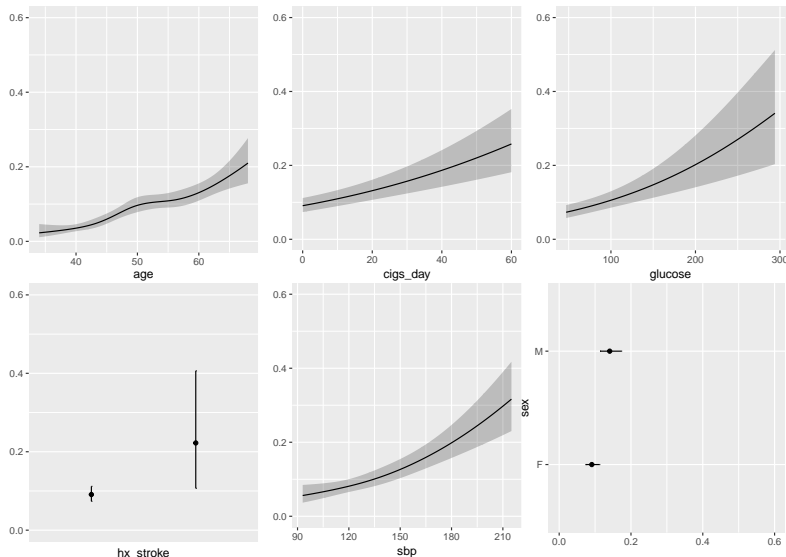
Can we see the prediction results?

```
ggplot(Predict(m_04_lrm),  
       anova = anova(m_04_lrm), pval = TRUE)
```



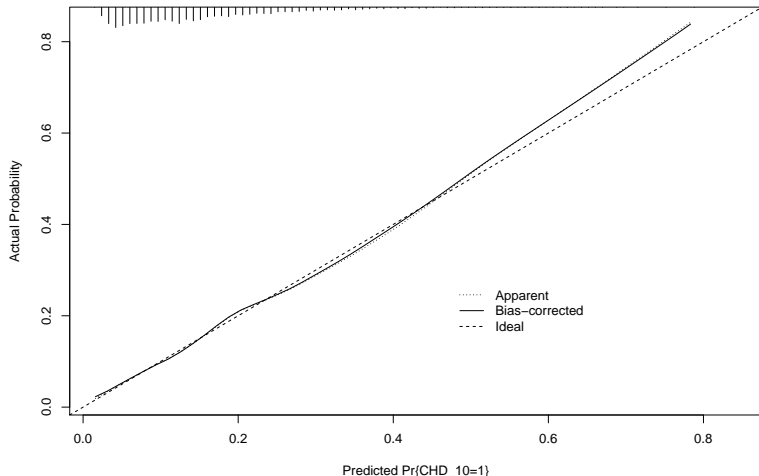
What about on a better scale?

```
ggplot(Predict(m_04_lrm, fun = plogis))
```



Calibration of mod_04_lrm

```
set.seed(432612); plot(calibrate(m_04_lrm))
```



B= 40 repetitions, boot

Mean absolute error=0.004 n=4240

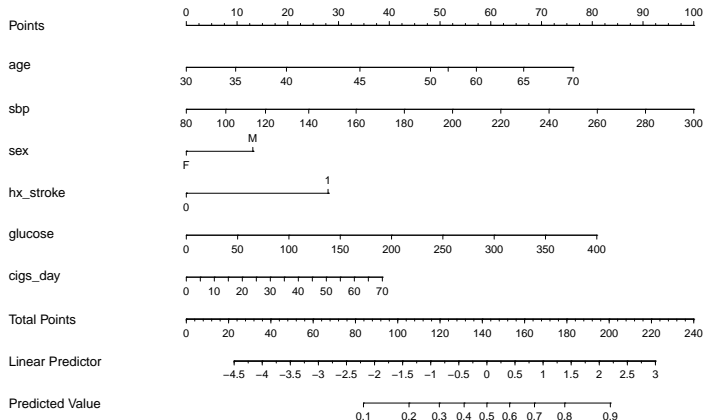
Goodness of fit test?

```
round(residuals(m_04_lrm, type = "gof"),3)
```

Sum of squared errors	Expected value H0
488.554	489.423
SD	Z
1.183	-0.735
P	
0.462	

Nomogram of mod_04_lrm

```
plot(nomogram(m_04_lrm, fun = plogis))
```



Comparing Models 3 and 4 (which aren't nested)

```
glance(m_03) # kitchen sink but no non-linear terms
```

	null.deviance	df.null	logLik	AIC	BIC
1	3612.209	4239	-1603.407	3242.813	3357.155

	deviance	df.residual
1	3206.813	4222

```
glance(m_04) # six predictors but with non-linear terms
```

	null.deviance	df.null	logLik	AIC	BIC	deviance
1	3612.209	4239	-1605.382	3232.764	3302.64	3210.764

	deviance	df.residual
1	4229	

Checking Residuals?

- Yes/No outcomes contain less information than quantitative outcomes
- Residuals cannot be observed - predicted
 - There are several different types of residuals defined
- Assumptions of logistic regression are different
 - Model is deliberately non-linear
 - Error variance is a function of the mean, so it isn't constant
 - Errors aren't assumed to follow a Normal distribution
 - Only thing that's the same: leverage and influence

So, plot 5 (residuals/leverage/influence) can be a little useful, but that's it.

- We'll need better diagnostic tools for generalized linear models.

Any observations particularly influential on Model 4?

```
which.influence(m_04_lrm, cutoff = 0.3)
```

```
$Intercept
```

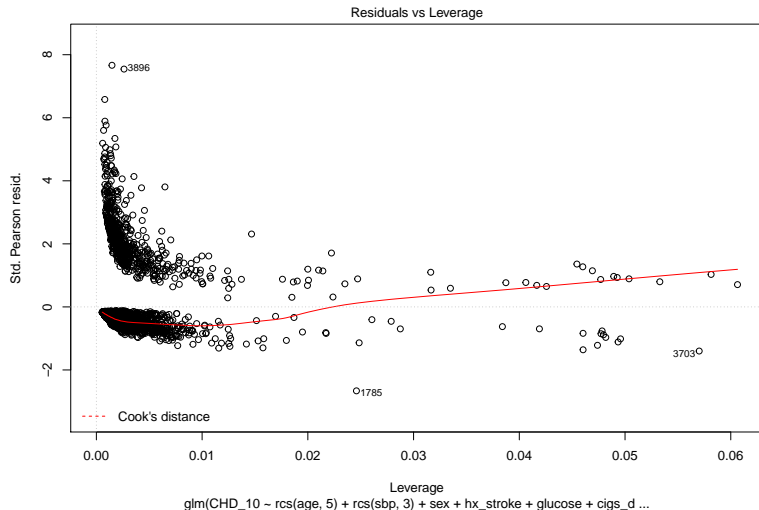
```
[1] "3896"
```

```
$glucose
```

```
[1] "1785" "3703"
```

Influence and Model 4?

```
plot(m_04, which = 5)
```



The HERS Trial

Hormone Therapy and Baseline LDL in the HERS Trial

HERS clinical trial of hormone therapy (HT). We're excluding the women with diabetes here.

```
hers <- read.csv("data/hersdata.csv") %>% tbl_df

hers1 <- hers %>%
  filter(diabetes == "no") %>%
  select(subject, LDL, HT, age, smoking, drinkany, SBP,
         physact, BMI, diabetes)
```

The Data

```
head(hers1)
```

```
# A tibble: 6 x 10
```

	subject	LDL	HT	age	smoking	drinkany	SBP	physact
	<int>	<dbl>	<fct>	<int>	<fct>	<fct>	<int>	<fct>
1	1	122	place~	70	no	no	138	much m~
2	2	242	place~	62	no	no	118	much l~
3	4	116	place~	64	yes	yes	152	much l~
4	5	151	place~	65	no	no	175	somewh~
5	6	138	hormo~	68	no	yes	174	about ~
6	8	121	hormo~	69	no	no	178	much m~

```
# ... with 2 more variables: BMI <dbl>, diabetes <fct>
```

The Codebook (n = 2,032 women without diabetes)

Variable	Description	Missing?
subject	subject code	0
LDL	LDL cholesterol in mg/dl	7
HT	factor: hormone therapy or placebo	0
age	age in years	0
smoking	yes or no	0
drinkany	yes or no	2
SBP	systolic BP in mm Hg	0
physact	5-level factor	0
BMI	body-mass index in kg/m ²	2
diabetes	yes or no (all of these are no)	0

Our Modeling Goal

Predict LDL using

- age
- smoking
- drinkany
- SBP
- physact
- BMI
- the interaction of smoking and BMI

Details on physact variable

```
hers1 %>% count(physact)
```

```
# A tibble: 5 x 2
```

	physact	n
	<fct>	<int>
1	about as active	674
2	much less active	107
3	much more active	252
4	somewhat less active	322
5	somewhat more active	677

Skim?

```
hers1 %>% select(-subject) %>% skim()
```

```
> hers1 %>% select(-subject) %>% skim()
```

Skim summary statistics



n obs: 2032

n variables: 9



Variable type: factor

variable	missing	complete	n	n_unique	top_counts	ordered
diabetes	0	2032	2032	1	no: 2032, yes: 0, NA: 0	FALSE
drinkany	2	2030	2032	2	no: 1135, yes: 895, NA: 2	FALSE
HT	0	2032	2032	2	pla: 1031, hor: 1001, NA: 0	FALSE
physact	0	2032	2032	5	som: 677, abo: 674, som: 322, muc: 252	FALSE
smoking	0	2032	2032	2	no: 1733, yes: 299, NA: 0	FALSE

Variable type: integer

variable	missing	complete	n	mean	sd	p0	p25	median	p75	p100	hist
age	0	2032	2032	66.89	6.75	44	62	67	72	79	
SBP	0	2032	2032	133.38	18.47	83	120	132	145	197	

Variable type: numeric

variable	missing	complete	n	mean	sd	p0	p25	median	p75	p100	hist
BMI	2	2030	2032	27.67	5.14	15.21	24.2	26.89	30.27	54.13	
LDL	7	2025	2032	145.65	37.07	36.8	120.6	141.4	166	351.2	

Missingness pattern?

```
na.pattern(hers1) # from Hmisc
```

```
pattern
```

```
0000000000 0000000010 0000010000 0100000000  
          2021          2          2          7
```

```
names(hers1)
```

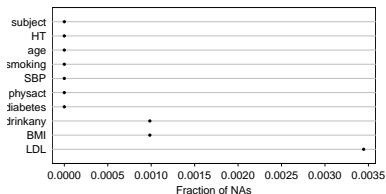
[1]	"subject"	"LDL"	"HT"	"age"	"smoking"
[6]	"drinkany"	"SBP"	"physact"	"BMI"	"diabetes"

Next slide

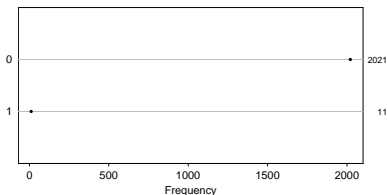
```
par(mfrow = c(2,2))  
naplot(naclus(hers1))  
par(mfrow = c(1,1))
```


naplot(naclus(hers1))

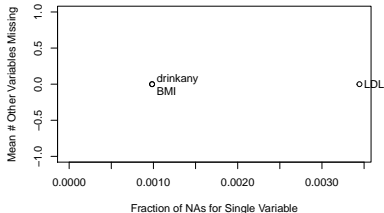
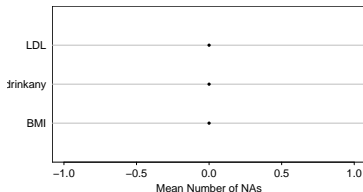
Fraction of NAs in each Variable



Number of Missing Variables Per Observation



Mean Number of Other Variables Missing for Observations where Indicated Variable is NA



Simple Imputation into `hers2`

Simple Imputation for drinkany, BMI and LDL

Since drinkany is a factor, we have to do some extra work to impute.

```
set.seed(432092)

hers2 <- hers1 %>%
  mutate(drinkany_n =
    ifelse(drinkany == "yes", 1, 0)) %>%
  impute_pmm(drinkany_n ~ age + smoking) %>%
  mutate(drinkany =
    ifelse(drinkany_n == 1, "yes", "no")) %>%
  impute_rlm(BMI ~ age + smoking + SBP) %>%
  impute_rlm(LDL ~ age + smoking + SBP + BMI)
```

Now, check missingness...

```
na.pattern(hers2)
```

```
pattern
000000000000
      2032
```

```
names(hers2)
```

```
[1] "subject"      "LDL"          "HT"           "age"
[5] "smoking"      "drinkany"     "SBP"          "physact"
[9] "BMI"          "diabetes"     "drinkany_n"
```

Multiple Imputation with aregImpute

Multiple Imputation using `aregImpute` from `Hmisc`

Model to predict all missing values of any variables, using additive regression bootstrapping and predictive mean matching.

Steps are:

- 1 `aregImpute` draws a sample with replacement from the observations where the target variable is observed, not missing.
- 2 It then fits a flexible additive model to predict this target variable while finding the optimum transformation of it.
- 3 It then uses this fitted flexible model to predict the target variable in all of the original observations.
- 4 Finally, it imputes each missing value of the target variable with the observed value whose predicted transformed value is closest to the predicted transformed value of the missing value.

Fitting a Multiple Imputation Model

```
set.seed(4320132)
dd <- datadist(hers1)
options(datadist = "dd")
fit3 <- aregImpute(~ LDL + age + smoking + drinkany +
                   SBP + physact + BMI,
                   nk = c(0, 3:5), tlinear = FALSE,
                   data = hers1, B = 10, n.impute = 20)
```

Iteration 1

Iteration 2

Iteration 3

Iteration 4

Iteration 5

Iteration 6

Iteration 7

Iteration 8

Iteration 9

Multiple Imputation using `aregImpute` from `Hmisc`

`aregImpute` requires specifications of all variables, and several other details:

- `n.impute` = number of imputations, we'll run 20
- `nk` = number of knots to describe level of complexity, with our choice `nk = c(0, 3:5)` we'll fit both linear models and models with restricted cubic splines with 3, 4, and 5 knots
- `tlinear = FALSE` allows the target variable to have a non-linear transformation when `nk` is 3 or more
- `B = 10` specifies 10 bootstrap samples will be used
- `data` specifies the source of the variables

aregImpute Imputation Results (1 of 3)

```
fit3
```

```
> fit3
```

Multiple Imputation using Bootstrap and PMM

```
aregImpute(formula = ~LDL + age + smoking + drinkany + SBP +  
  physact + BMI, data = hers1, n.impute = 20, nk = c(0, 3:5),  
  tlinear = FALSE, B = 10)
```

n: 2032 p: 7 Imputations: 20 nk: 0

Number of NAs:

LDL	age	smoking	drinkany	SBP	physact	BMI
7	0	0	2	0	0	2

	type	d.f.
--	------	------

LDL	s	1
age	s	1
smoking	c	1
drinkany	c	1
SBP	s	1
physact	c	4
BMI	s	1

aregImpute Imputation Results (2 of 3)

R-squares for Predicting Non-Missing Values for Each Variable
Using Last Imputations of Predictors

	LDL	drinkany	BMI
	0.019	0.029	0.093

Resampling results for determining the complexity of imputation models

Variable being imputed: LDL

			nk=0	nk=3	nk=4	nk=5
Bootstrap bias-corrected	R ²		0.0151	0.0149	0.0101	0.00976
10-fold cross-validated	R ²		0.0154	0.0224	0.0129	0.01913
Bootstrap bias-corrected	mean	error	28.2956	42.5462	43.9458	39.56345
10-fold cross-validated	mean	error	145.8339	43.2577	44.8477	45.07517
Bootstrap bias-corrected	median	error	22.7110	35.0460	38.9420	32.95988
10-fold cross-validated	median	error	142.1896	35.3638	38.3446	38.08496

aregImpute Imputation Results (3 of 3)

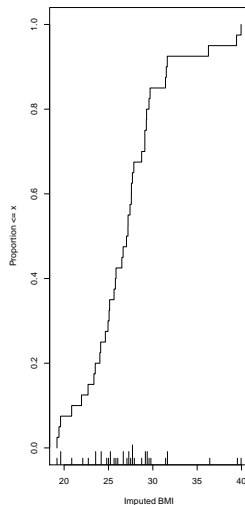
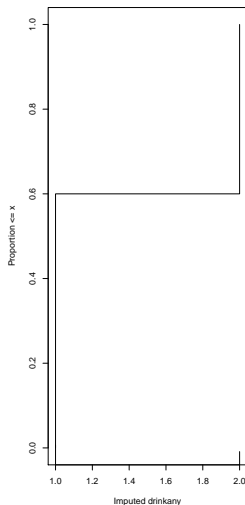
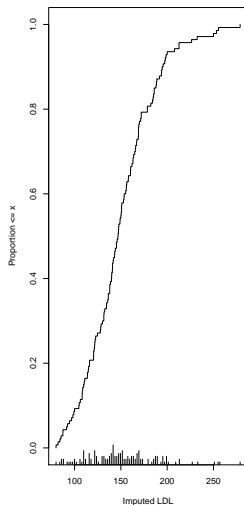
Variable being imputed: drinkany

		nk=0	nk=3	nk=4	nk=5
Bootstrap bias-corrected	R ²	0.0138	0.0110	0.0131	0.0104
10-fold cross-validated	R ²	0.0191	0.0184	0.0182	0.0122
Bootstrap bias-corrected	mean error	0.4535	0.4529	0.4551	0.4567
10-fold cross-validated	mean error	0.4482	0.4499	0.4382	0.4644
Bootstrap bias-corrected	median error	0.0000	0.0000	0.0000	0.0000
10-fold cross-validated	median error	0.2000	0.3000	0.0000	0.2000

Variable being imputed: BMI

		nk=0	nk=3	nk=4	nk=5
Bootstrap bias-corrected	R ²	0.0851	0.0878	0.0858	0.0892
10-fold cross-validated	R ²	0.0880	0.0940	0.0930	0.0923
Bootstrap bias-corrected	mean error	3.8316	4.8352	4.9466	5.1806
10-fold cross-validated	mean error	27.6718	4.8115	4.9504	4.9765
Bootstrap bias-corrected	median error	2.9944	4.0176	4.0021	4.2517
10-fold cross-validated	median error	27.0170	4.0261	3.9930	4.0836

A plot of the imputed values... (results)



A plot of the imputed values... (code)

```
par(mfrow = c(1,3))  
plot(fit3)  
par(mfrow = c(1,1))
```

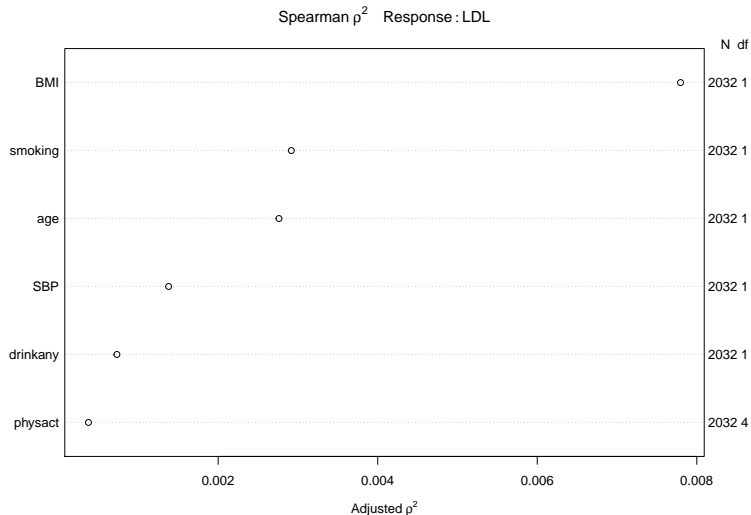
- For LDL, we imputed most of the 7 missing subjects in most of the 20 imputation runs to values within a range of around 120 through 200, but occasionally, we imputed values that were substantially lower than 100.
- For `drinkany` we imputed about 70% no and 30% yes.
- For BMI, we imputed values ranging from about 23 to 27 in many cases, and up near 40 in other cases.
- This method never imputes a value for a variable that doesn't already exist in the data.

Spearman ρ^2 Plot

We've already decided to include a BMI*smoking product term, but how should we prioritize the degrees of freedom we spend on non-linearity otherwise?

```
plot(spearman2(LDL ~ age + smoking + drinkany + SBP +  
              physact + BMI, data = hers2))
```

Spearman ρ^2 Plot Result



Fitting a Linear Regression with `ols`

Model we'll fit

Fitting a model to predict LDL using

- BMI with a restricted cubic spline, 5 knots
- age with a quadratic polynomial
- SBP as a linear term
- drinkany indicator
- physact factor
- smoking indicator and its interaction with BMI

We could fit this to the data

- restricted to complete cases (hers1, effectively)
- after simple imputation (hers2)
- after our multiple imputation (fit3)

Fitting the model after simple imputation

```
dd <- datadist(hers2)
options(datadist = "dd")

m2 <- ols(LDL ~ rcs(BMI, 5) + pol(age, 2) + SBP +
          drinkany + physact + smoking +
          smoking %ia% BMI, data = hers2,
          x = TRUE, y = TRUE)
```

where %ia% identifies the linear interaction alone.

m2 results (slide 1 of 2)

```
> m2
Linear Regression Model

ols(formula = LDL ~ rcs(BMI, 5) + pol(age, 2) + SBP + drinkany +
      physact + smoking + smoking %ia% BMI, data = hers2, x = TRUE,
      y = TRUE)
```

		Model Likelihood		Discrimination	
		Ratio Test		Indexes	
Obs	2032	LR chi2	53.14	R2	0.026
sigma	36.6503	d.f.	14	R2 adj	0.019
d.f.	2017	Pr(> chi2)	0.0000	g	6.631

Residuals

	Min	1Q	Median	3Q	Max
	-113.379	-24.326	-3.835	20.832	197.097

m2 results (slide 2 of 2)

	Coef	S.E.	t	Pr(> t)
Intercept	120.2662	67.6113	1.78	0.0754
BMI	1.5508	1.0071	1.54	0.1237
BMI'	-8.4486	9.0978	-0.93	0.3532
BMI''	39.6413	37.1378	1.07	0.2859
BMI'''	-54.8924	44.2677	-1.24	0.2151
age	-0.5249	1.9490	-0.27	0.7877
age^2	0.0014	0.0148	0.10	0.9233
SBP	0.1209	0.0451	2.68	0.0074
drinkany=yes	-3.7023	1.6544	-2.24	0.0253
physact=much less active	-4.7408	3.8621	-1.23	0.2198
physact=much more active	-0.2635	2.7391	-0.10	0.9234
physact=somewhat less active	0.0130	2.5101	0.01	0.9959
physact=somewhat more active	3.8031	2.0193	1.88	0.0598
smoking=yes	-6.8961	12.0196	-0.57	0.5662
smoking=yes * BMI	0.4892	0.4375	1.12	0.2636

Validation of summary statistics

```
validate(m2)
```

	index.orig	training	test	optimism
R-square	0.0258	0.0307	0.0188	0.0119
MSE	1333.3300	1320.0677	1342.9027	-22.8350
g	6.6306	7.1548	5.8726	1.2821
Intercept	0.0000	0.0000	26.2153	-26.2153
Slope	1.0000	1.0000	0.8208	0.1792

	index.corrected	n
R-square	0.0139	40
MSE	1356.1650	40
g	5.3485	40
Intercept	26.2153	40
Slope	0.8208	40

anova(m2) results

```
> anova(m2)
```

	Analysis of Variance		Response: LDL		
Factor	d.f.	Partial SS	MS	F	P
BMI (Factor+Higher Order Factors)	5	2.758824e+04	5517.64861	4.11	0.0010
All Interactions	1	1.679813e+03	1679.81344	1.25	0.2636
Nonlinear	3	9.735452e+03	3245.15068	2.42	0.0647
age	2	9.175762e+03	4587.88077	3.42	0.0330
Nonlinear	1	1.244351e+01	12.44351	0.01	0.9233
SBP	1	9.657476e+03	9657.47569	7.19	0.0074
drinkany	1	6.726918e+03	6726.91809	5.01	0.0253
physact	4	9.709992e+03	2427.49791	1.81	0.1247
smoking (Factor+Higher Order Factors)	2	1.085405e+04	5427.02463	4.04	0.0177
All Interactions	1	1.679813e+03	1679.81344	1.25	0.2636
smoking * BMI (Factor+Higher Order Factors)	1	1.679813e+03	1679.81344	1.25	0.2636
TOTAL NONLINEAR	4	9.738807e+03	2434.70175	1.81	0.1237
TOTAL NONLINEAR + INTERACTION	5	1.171134e+04	2342.26845	1.74	0.1214
REGRESSION	14	7.178905e+04	5127.78931	3.82	<.0001
ERROR	2017	2.709327e+06	1343.24569		

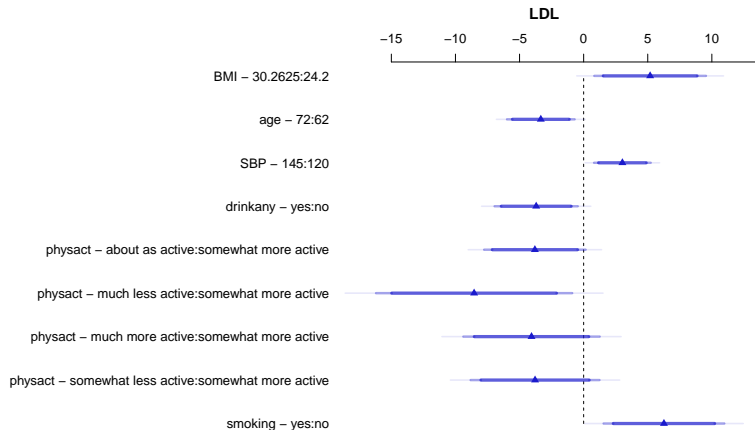
summary(m2) results

```
> summary(m2)
```

Effects	Response : LDL							
Factor	Low	High	Diff.	Effect	S.E.	Lower 0.95	Upper 0.95	
BMI	24.2	30.263	6.0625	5.1862	2.2217	0.82921	9.54330	
age	62.0	72.000	10.0000	-3.3412	1.3450	-5.97890	-0.70357	
SBP	120.0	145.000	25.0000	3.0218	1.1270	0.81165	5.23190	
drinkany - yes:no	1.0	2.000	NA	-3.7023	1.6544	-6.94690	-0.45779	
physact - about as active:somewhat more active	5.0	1.000	NA	-3.8031	2.0193	-7.76310	0.15695	
physact - much less active:somewhat more active	5.0	2.000	NA	-8.5439	3.9035	-16.19900	-0.88862	
physact - much more active:somewhat more active	5.0	3.000	NA	-4.0666	2.7125	-9.38630	1.25310	
physact - somewhat less active:somewhat more active	5.0	4.000	NA	-3.7901	2.5633	-8.81720	1.23690	
smoking - yes:no	1.0	2.000	NA	6.2635	2.4009	1.55500	10.97200	

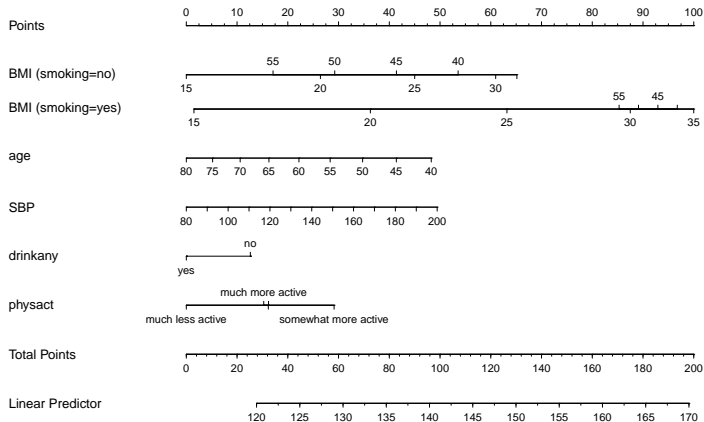
Adjusted to: BMI=26.9 smoking=no

plot(summary(m2)) results



Adjusted to: BMI=26.9 smoking=no

plot(nomogram(m2))



Making Predictions for an Individual

Suppose now that we want to use R to get a prediction for a new individual subject with BMI = 30, age = 50, smoking = yes and physact = about as active, drinkany= yes and SBP of 150.

```
predict(m2, expand.grid(BMI = 30, age = 50, smoking = "yes",  
                        physact = "about as active",  
                        drinkany = "yes", SBP = 150),  
        conf.int = 0.95, conf.type = "individual")
```

\$linear.predictors	\$lower	\$upper
160.9399	88.48615	233.3936

Making Predictions for a Long-Run Mean

The other kind of prediction we might wish to make is for the mean of a series of subjects whose BMI = 30, age = 50, smoking = yes and physact = about as active, drinkany= yes and SBP of 150.

```
predict(m2, expand.grid(BMI = 30, age = 50, smoking = "yes",  
                        physact = "about as active",  
                        drinkany = "yes", SBP = 150),  
        conf.int = 0.95, conf.type = "mean")
```

\$linear.predictors	\$lower	\$upper
160.9399	151.8119	170.0679

Of course, the confidence interval will always be narrower than the prediction interval given the same predictor values.

Influential Points?

```
which.influence(m2, cutoff = 0.4)
```

```
$Intercept
```

```
[1] 1135
```

```
$age
```

```
[1] 1135
```

```
$smoking
```

```
[1] 132
```

```
$`smoking * BMI`
```

```
[1] 132
```

Fitting the model to the complete cases

```
d <- datadist(hers1)
options(datadist = "d")

m1 <- ols(LDL ~ rcs(BMI, 5) + pol(age, 2) + SBP +
          drinkany + physact + smoking +
          smoking %ia% BMI, data = hers1,
          x = TRUE, y = TRUE)
```

where %ia% identifies the linear interaction alone.

Putting it Together

What have we got?

- An imputation model `fit3`

```
fit3 <- aregImpute(~ LDL + age + smoking + drinkany + SBP +  
  physact + BMI, nk = c(0, 3:5), tlinear = FALSE,  
  data = hers1, B = 10, n.impute = 20, x = TRUE)
```

- A prediction model

```
m1 <- ols(LDL ~ rcs(BMI, 5) + pol(age, 2) + SBP +  
  drinkany + physact + smoking + smoking %ia% BMI,  
  x = TRUE, y = TRUE)
```

Now we put them together

Linear Regression & Imputation Model

```
m3imp <-  
  fit.mult.impute(LDL ~ rcs(BMI, 5) + pol(age, 2) + SBP +  
    drinkany + physact + smoking +  
    smoking %ia% BMI,  
    fitter = ols, xtrans = fit3,  
    data = hers1)
```

Variance Inflation Factors Due to Imputation:

Intercept	BMI
1.00	1.00
BMI '	BMI ' '
1.00	1.00
BMI ' ' '	age
1.00	1.00
age^2	SBP

m3imp results (1 of 2)

```
> m3imp
```

```
Linear Regression Model
```

```
fit.mult.impute(formula = LDL ~ rcs(BMI, 5) + pol(age, 2) + SBP +  
  drinkany + physact + smoking + smoking %ia% BMI, fitter = ols,  
  xtrans = fit3, data = hers1)
```

		Model Likelihood		Discrimination	
		Ratio Test		Indexes	
Obs	2032	LR chi2	53.30	R2	0.026
sigma	36.7128	d.f.	14	R2 adj	0.019
d.f.	2017	Pr(> chi2)	0.0000	g	6.652

```
Residuals
```

Min	1Q	Median	3Q	Max
-113.10	-24.46	-3.81	20.92	197.42

m3imp results (2 of 2)

	Coef	S.E.	t	Pr(> t)
Intercept	121.1499	67.7998	1.79	0.0741
BMI	1.5445	1.0097	1.53	0.1263
BMI'	-8.2945	9.1027	-0.91	0.3623
BMI''	39.0890	37.3055	1.05	0.2949
BMI'''	-54.2119	44.4779	-1.22	0.2230
age	-0.5521	1.9547	-0.28	0.7776
age^2	0.0016	0.0148	0.11	0.9119
SBP	0.1216	0.0453	2.69	0.0073
drinkany=yes	-3.7404	1.6625	-2.25	0.0246
physact=much less active	-4.7426	3.8692	-1.23	0.2204
physact=much more active	-0.2665	2.7455	-0.10	0.9227
physact=somewhat less active	0.0313	2.5214	0.01	0.9901
physact=somewhat more active	3.8060	2.0257	1.88	0.0604
smoking=yes	-6.9198	12.0472	-0.57	0.5658
smoking=yes * BMI	0.4917	0.4388	1.12	0.2626

anova(m3imp)

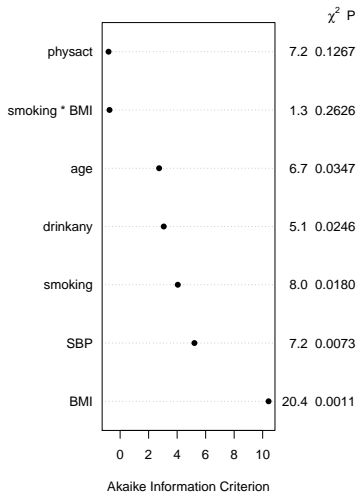
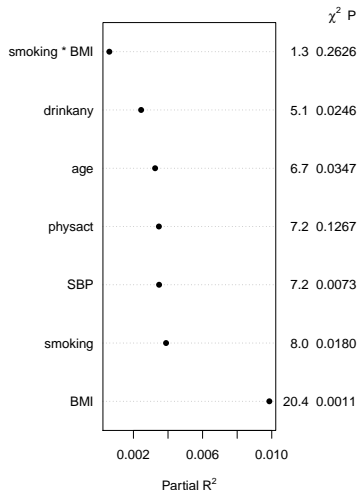
```
> anova(m3imp)
```

Analysis of Variance

Response: LDL

Factor	d.f.	Partial SS	MS	F	P
BMI (Factor+Higher Order Factors)	5	27514.6406	5502.9281	4.08	0.0011
All Interactions	1	1692.6044	1692.6044	1.26	0.2626
Nonlinear	3	9741.6194	3247.2065	2.41	0.0653
age	2	9078.9851	4539.4926	3.37	0.0347
Nonlinear	1	16.5032	16.5032	0.01	0.9119
SBP	1	9721.1667	9721.1667	7.21	0.0073
drinkany	1	6822.3861	6822.3861	5.06	0.0246
physact	4	9690.3632	2422.5908	1.80	0.1267
smoking (Factor+Higher Order Factors)	2	10845.6127	5422.8063	4.02	0.0180
All Interactions	1	1692.6044	1692.6044	1.26	0.2626
smoking * BMI (Factor+Higher Order Factors)	1	1692.6044	1692.6044	1.26	0.2626
TOTAL NONLINEAR	4	9747.0966	2436.7741	1.81	0.1246
TOTAL NONLINEAR + INTERACTION	5	11717.3715	2343.4743	1.74	0.1225
REGRESSION	14	71571.1297	5112.2236	3.79	<.0001
ERROR	2017	2718570.0412	1347.8285		

Evaluation via Partial R² and AIC (result)



Evaluation via Partial R^2 and AIC (code)

```
par(mfrow = c(1,2))  
plot(anova(m3imp), what="partial R2")  
plot(anova(m3imp), what="aic")  
par(mfrow = c(1,1))
```

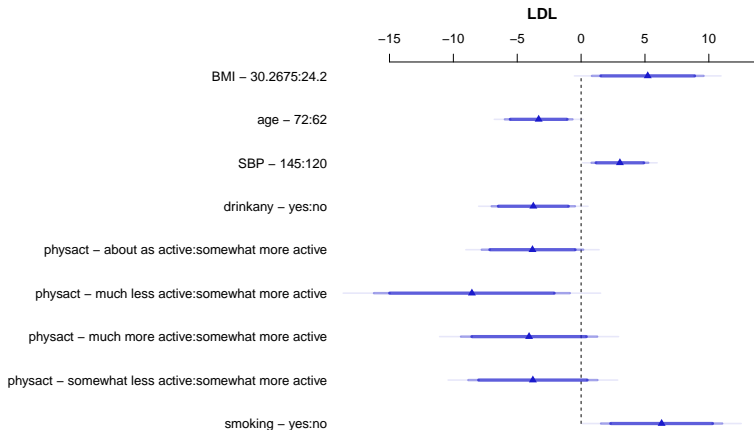
summary(m3imp)

```
> summary(m3imp)
```

Effects	Response : LDL						
Factor	Low	High	Diff.	Effect	S.E.	Lower 0.95	Upper 0.95
BMI	24.2	30.268	6.0675	5.2165	2.2287	0.84565	9.58730
age	62.0	72.000	10.0000	-3.3219	1.3498	-5.96910	-0.67463
SBP	120.0	145.000	25.0000	3.0394	1.1317	0.81989	5.25880
drinkany - yes:no	1.0	2.000	NA	-3.7404	1.6625	-7.00080	-0.47996
physact - about as active:somewhat more active	5.0	1.000	NA	-3.8060	2.0257	-7.77860	0.16663
physact - much less active:somewhat more active	5.0	2.000	NA	-8.5486	3.9114	-16.21900	-0.87779
physact - much more active:somewhat more active	5.0	3.000	NA	-4.0724	2.7198	-9.40640	1.26160
physact - somewhat less active:somewhat more active	5.0	4.000	NA	-3.7746	2.5773	-8.82900	1.27980
smoking - yes:no	1.0	2.000	NA	6.3043	2.4196	1.55900	11.05000

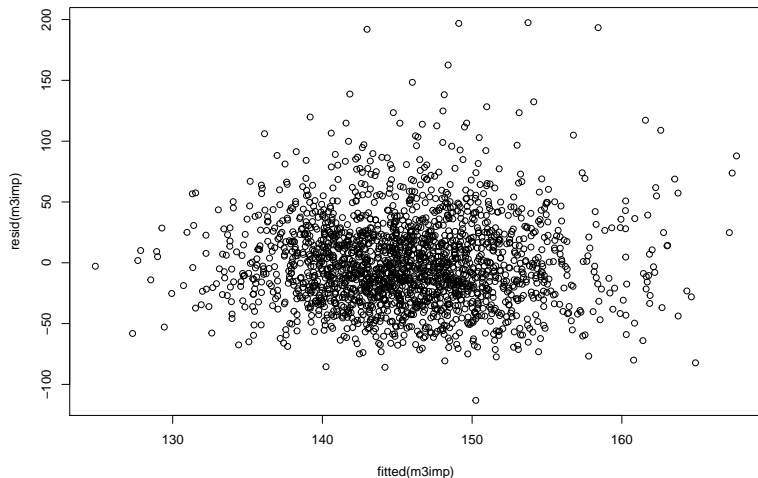
Adjusted to: BMI=26.895 smoking=no

```
plot(summary(m3imp))
```



Adjusted to: BMI=26.895 smoking=no

```
plot(resid(m3imp) ~ fitted(m3imp))
```



plot(nomogram(m3imp))

