Group 3: Data Analysis

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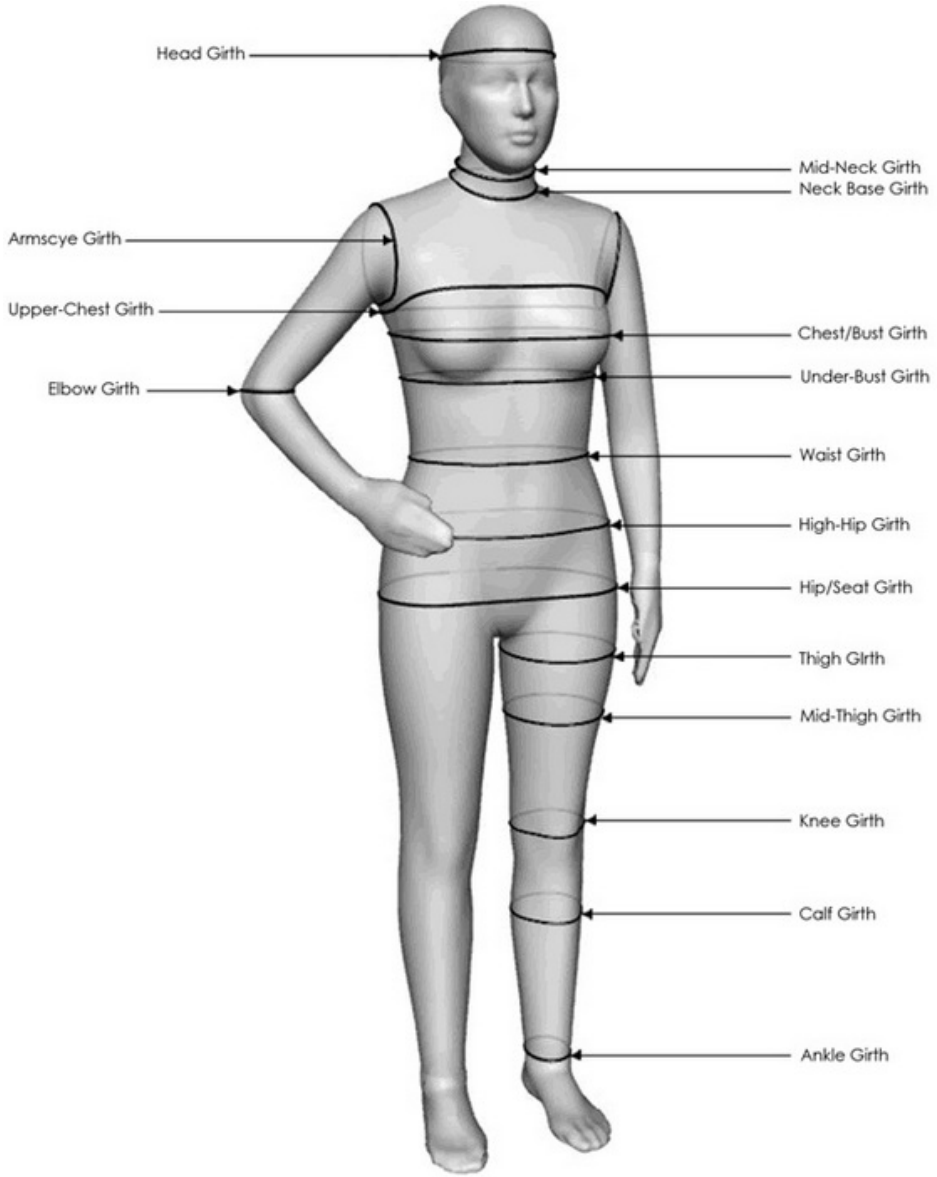
Introduction

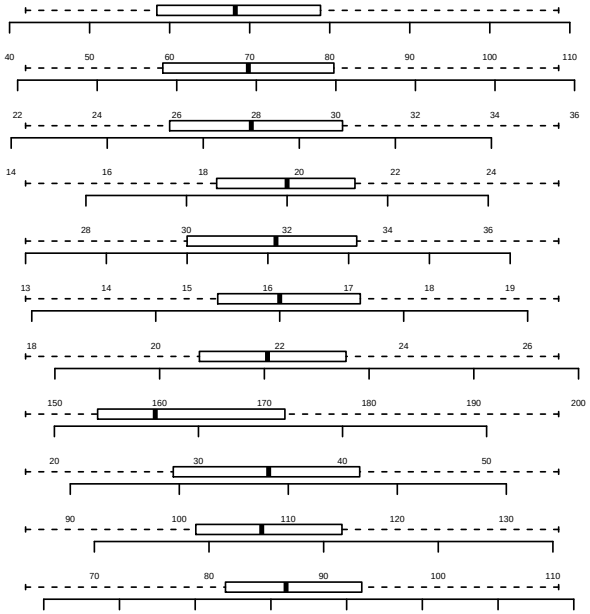
- The dataset, "Exploring Relationships in Body Dimensions", contains 25 variables: 21 body dimension measurements as well as age, weight, height, and gender for 507 physically active, young individuals.
- Of the body dimension measurements, 9 were skeletal/diameter measurements and 12 were girth/circumference measurements.
- Of the 507 individual observations, there are 247 men and 260 women.
- No missing values. Measurements made with metric scale.



Description of Variables

Summary table(left) Boxplot(right)

variable	Min.	Median	Mean	Max.
weight	42.00	68.20	69.15	116.40
chest.diam	22.20	27.80	27.97	35.60
chest.dep	14.30	19.00	19.23	27.50
bitro.diam	24.70	32.00	31.98	38.00
wrist.min	13.00	16.10	16.10	19.60
ankle.min	16.40	22.00	22.16	29.30
height	147.20	170.30	171.10	198.10
age	18.00	27.00	30.18	67.00
shoulder	85.90	108.20	108.20	134.80
navel	64.00	84.60	85.65	121.10
hip	78.80	96.00	96.68	128.30



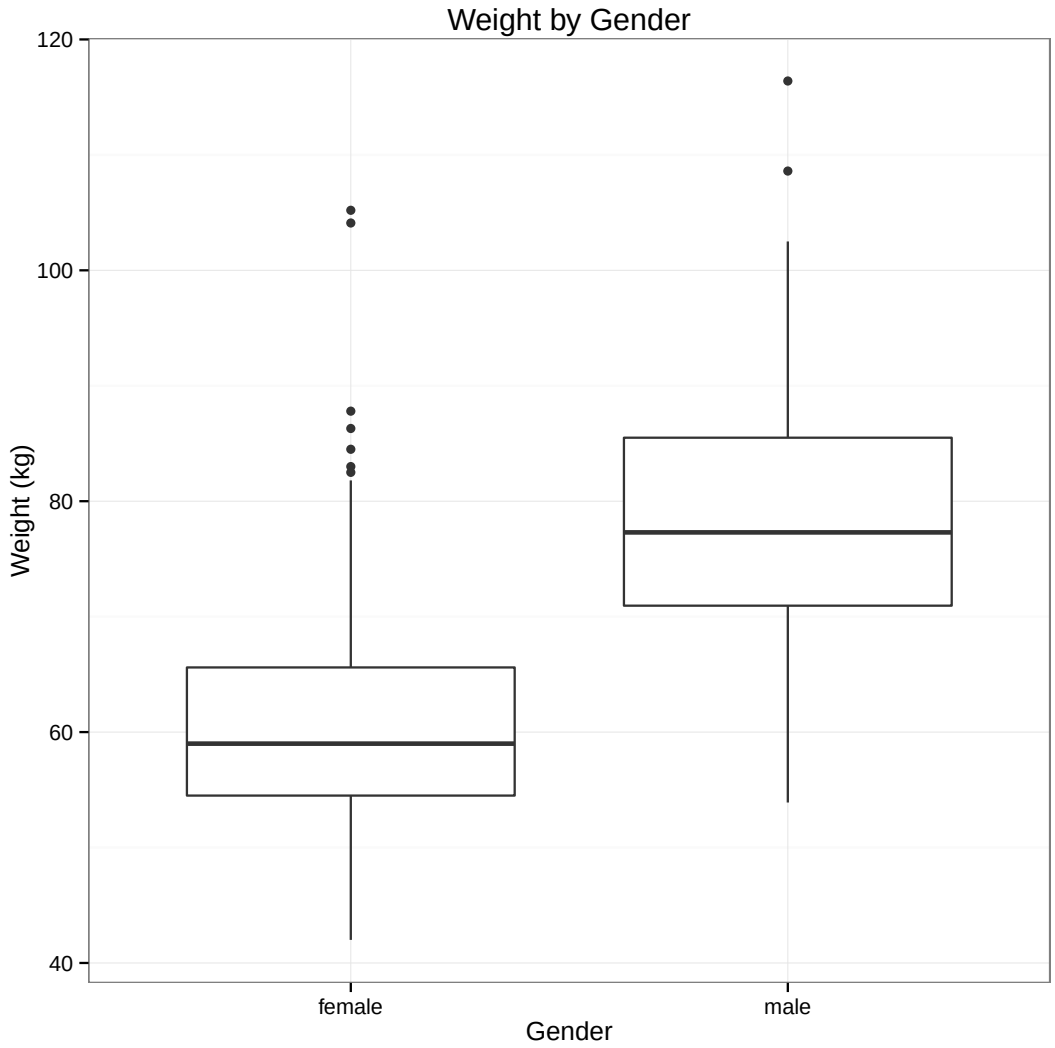
Text summary about the table

Outcome of Interest: Weight

Applications of Data:

- investigate correspondence of frame size, girths, and weight of young, athletic people
- estimate ideal weight
- inform predictions of lean/fat body compositions
- identify gender in forensic science
- design appropriate clothing (law enforcement/military)

Note: Outliers in the distribution of weight may be present because some of the individuals had unusually high muscle mass due to their high level of physical fitness.



Multiple Linear Regression Model

Initial Model

$$\begin{aligned} \text{weight}_i &= \beta_0 + \beta_1 \text{chest.diam}_i + \beta_2 \text{chest.dep}_i + \beta_3 \text{bitro.diam}_i \\ &\quad + \beta_4 \text{wrist.min}_i + \beta_5 \text{ankle.min}_i + \beta_6 \text{height}_i \end{aligned}$$

R Output:

(Intercept)	chest.diam	chest.dep	bitro.diam	wrist.min	ankle.min	height
-109.89	1.34	1.54	1.20	1.11	1.15	0.18

- This model was chosen by the authors of the dataset based on the idea that these measurements remain constant after physical maturation.
- It seems that, in our model, chest depth has the largest impact on weight.
- COMMENTS ABOUT GOODNESS OF FIT???

Model Selection Criteria and Methods (Emily)

The methods used to create ten different models were: include all variables (1), suggested by paper (2), my selection (1), stepAIC (1), leaps (2) and combinations of R functions and human selection (3).

The seclection criterions used to analyse the models are AIC, BIC, PRESS and Adjusted R^2. AIC and BIC measure goodness-of-fit through residual sum of squares (log likelihoods) and penalizes the model size; the smaller the AIC/BIC, the better. Adjusted R^2 adjusts R^2 so that the model is penalized for adding more predictors; the higher the value of the adjusted R^2 the better. Finally, PRESS is a summary measure focused on prediction; the lower the value of PRESS, the better.

My Selection (Emily)

Predictors needed are age, height and gender. These variables contribute significantly to weight. The predictors we will allow in model selection are the predictors used in the inital model: chest diameter, chest depth and bitro diameter.
Predictors I will allow are pelvic bredth, shoulder, chest, waist, hip and thigh will be used. I chose to allow these predictors in the model since these are directly associated with weight (e.g. waist).
After running a few combinations using these variables, the model I decided was the "best" includes the predictors chest.dep, chest.diam, shoulder, waist, hip, thight and height^2;
The quadratic term for height was used since height is a significant variable. This model is deemed as the best since it has the lowest BIC and AIC values of the few models I tried.

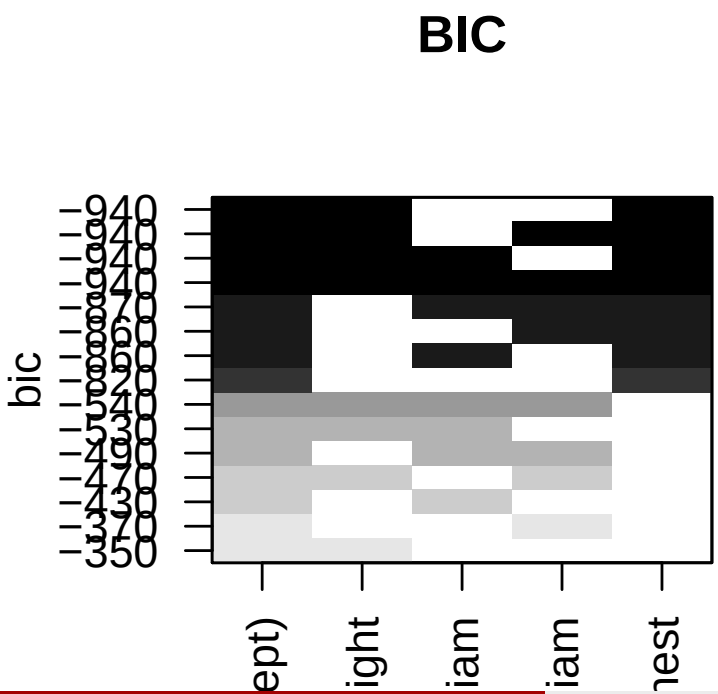
R function: stepAIC() (Emily)

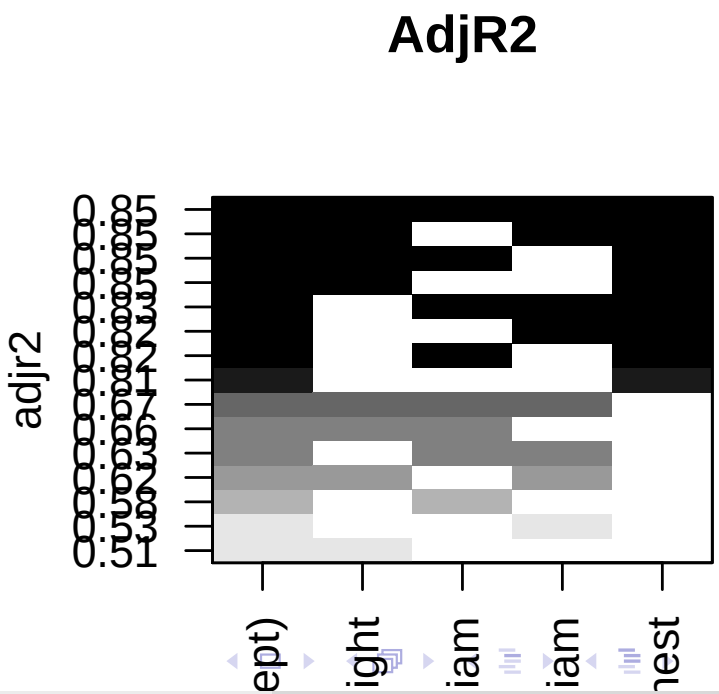
```
MLRex <- lm(weight   height + wrist.min + ankle.min + chest,
data = body) step <- stepAIC(MLRex, direction = "both")
```

```
head(stepanova)
```

R function: leaps() (Emily)

```
leaps <- regsubsets(weight   height + wrist.diam + ankle.diam
+ chest, nbest = 10, data = body)
par(mfrow = c(1, 2)) plot(leaps, main = "BIC") plot(leaps, sca
= "adjr2", main = "AdjR2")
```





Summary (Emily)

Table 2: Criteria Summary for each model

MLR#	AIC	BIC	PRESS	Adjusted R^2	Method
all	2216	2326	2384	0.9753	all variables from dataset used
i	2970	3004	10405	0.8869	suggested by paper
1	2256	2319	2560	0.9727	suggested by paper
2	2402	2441	3408	0.9632	my model
3	2206	2282	2329	0.9754	stepAIC
4	2195	2271	2281	0.9759	stepAIC and adjustments
5	2207	2292	2335	0.9755	leaps (adj R^2)
6	2189	2278	2255	0.9764	leaps(adj R^2)and adjustments
7	2213	2272	2353	0.9749	leaps(BIC)
8	2205	2264	2316	0.9753	leaps(BIC) and adjustments

Red corresponds to the best value for that criteria, blue is the second best.

- Model Selection truely is an art form.
- R can mechanically run through steps, interactions, combinations, etc.
- R cannot subjectively look at the variables to determine the absolute best model.
- To acheive the model of "best" fit, it is best to utilize a combination of R functions, criteria methods, and your own adjustments/ intuition.

Nick

Nick

Model Selection (Yiding)

Logistic Model: $logit(p_i) = \beta_0 + \beta_1 X_{i1} + ... + \beta_m X_{im}$

Model selection criteria:

- *AIC*
  $= nlog(RRS/n) + 2(p+1)$
  in R: *step*()

AIC criteria model selection

Step #	Model	AIC
1	*logi*(SEX)=WT+CDM+CDP+BDM+WR+ANK+HT+AGE+SHD+NAV+HIP	110.35
2	*logi*(SEX)=WT+CDP+BDM+WR+ANK+HT+AGE+SHD+NAV+HIP	108.36
3	*logi*(SEX)=WT+CDP+BDM+WR+HT+AGE+SHD+NAV+HIP	106.45
4	*logi*(SEX)=CDP+BDM+WR+HT+AGE+SHD+NAV+HIP	104.55
5	*logi*(SEX)=CDP+WR+HT+AGE+SHD+NAV+HIP	102.69
6	*logi*(SEX)=CDP+WR+HT+AGE+SHD+HIP	101.05

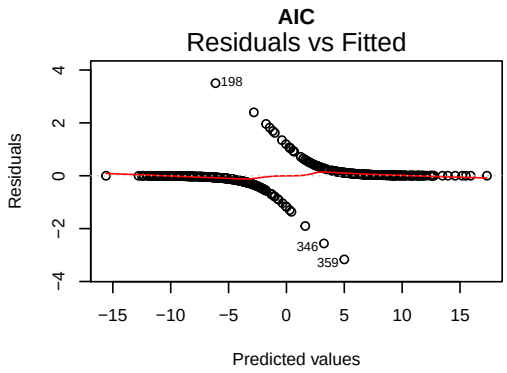
- *BIC*
  $= nlog(RSS/n) + (p+1)log(n)$
  &
  Posterior Probability
  $= p(\theta \mid x) = \frac{p(x|\theta)p(\theta)}{p(x)}$
  in R: *BMA* packages *bic.glm*()

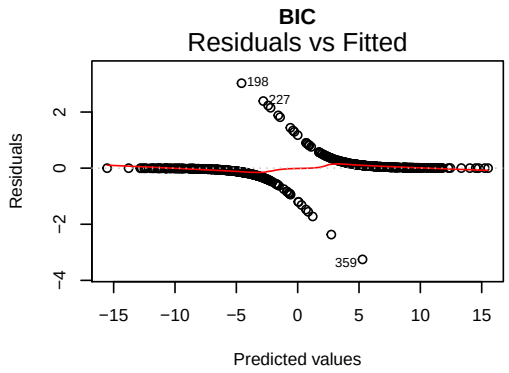
BIC criteria model selection

Model #	Model	BIC	Posterior prob
1	*logi*(SEX)=WR+HT+SHD+HIP	-3033	0.453
2	*logi*(SEX)=WR+HT+AGE+SHD+HIP	-3031	0.157
3	*logi*(SEX)=CDP+WR+HT+AGE+SHD+HIP	-3031	0.151
4	*logi*(SEX)=WR+HT+SHD+NAV+HIP	-3031	0.142
5	*logi*(SEX)=WR+HT+SHD+HIP	-3029	0.047

Check the Goodness of Model (Yiding)

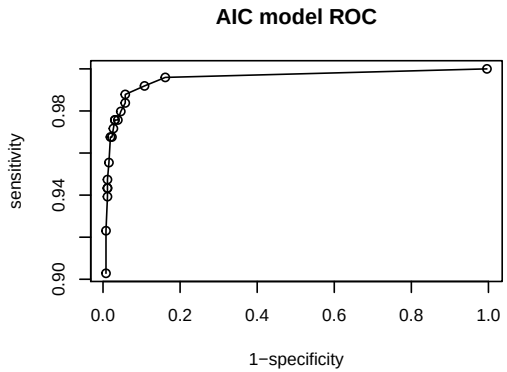
- **Linearity**
  Residuals vs Fitted Values
  Pearson residuals:
  $r_i = \frac{y_i - \hat{\mu}_i}{\sqrt{\hat{V}(y_i)}} = \frac{y_i - n_i\hat{\pi}_i}{\sqrt{n_i\hat{\pi}_i(1-\hat{\pi}_i)}}$

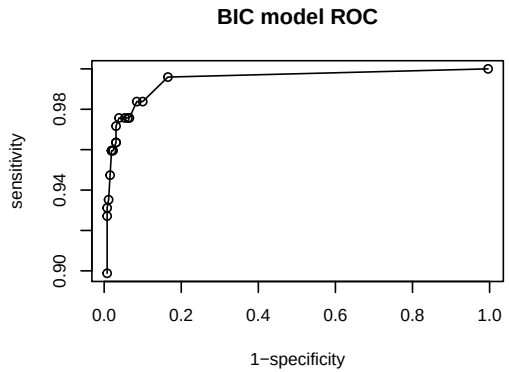




- **Predictive ability**
  ROC curve:
  sinsitivity *vs* 1-specificity
  Somer's rank correlation:
  $D_{xy} = 2(c - 0.5)$
  c is the area under the ROC curve.

  Hmisc package: *somers2*()





Model	Area ROC curve	Somers' D_{xy}
AIC	0.9944721	0.9889443
BIC	0.9941607	0.9883214

Ada-boosting (Yiding)

Algorithem:

Given: $(x_1, y_1), \ldots, (x_m, y_m)$ where

$x_i \in X, y_i \in Y = \{-1, +1\}$ Initialize

$D_1(i) = 1/m$.

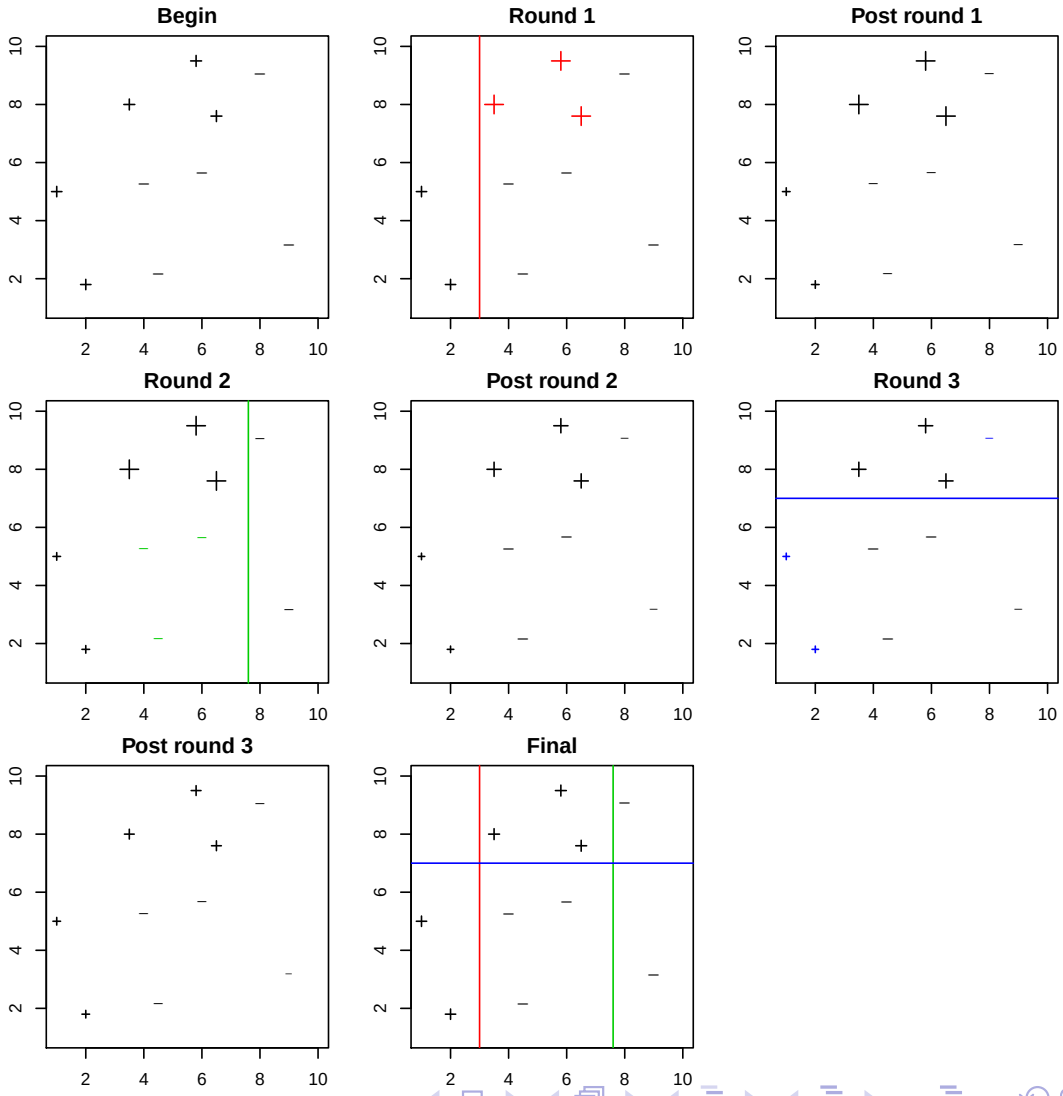
For $t = 1, \ldots, T$:

- Train weak learner using distribution D_t.
- Get weak hypothesis $h_t : X \to \{-1, +1\}$ with error $\epsilon_t = Pr_{i \sim D_t}[h_t(x_i) \neq y_i]$
- Choose $\alpha_t = \frac{1}{2} ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$
- Update:

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \begin{cases} e^{-\alpha_t} & \text{if } h_t(x_i) = y_i \\ e^{\alpha_t} & \text{if } h_t(x_i) \neq y_i \end{cases}$$

$$= \frac{D_i(i) exp(\alpha_t y_i h_t(x_i))}{Z_t}$$

Final hypothesis: $H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$



Logistic Regression vs Ada-boosting (Yiding)

Logistic Regression
Predictive ability depends on cutoff point

Cutoff point	Sensitivity	Specificity
0.00	1.000	0.004
0.05	0.996	0.838
0.10	0.992	0.892
0.15	0.988	0.942
0.20	0.984	0.954
...	...	...
0.85	0.923	0.992
0.90	0.903	0.992

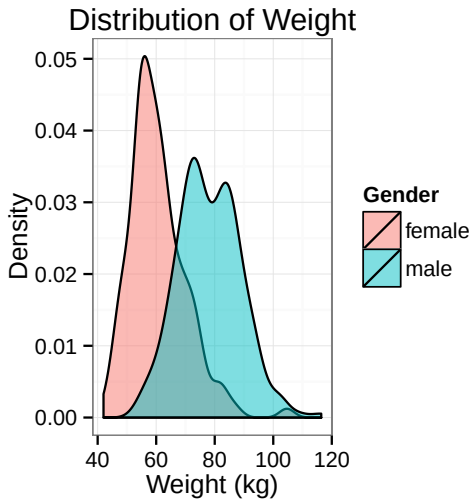
Ada-boosting
Predictive ability depends on variables

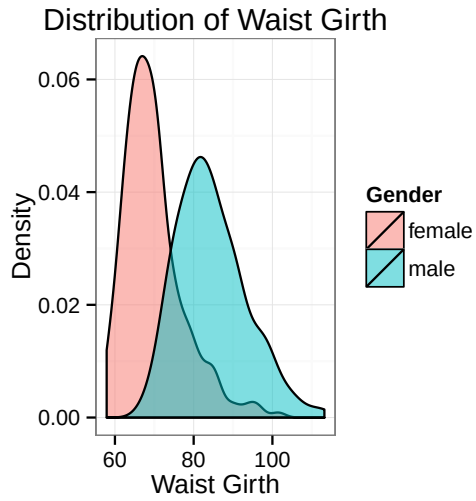
Round #	Original data	AIC data	BIC data
	Sensitiviy; Specificity; Accuracy	Sensitiviy; Specificity; Accuracy	Sensitiviy; Specificity; Accuracy
1	0.975; 0.925; 0.949	0.967; 0.962; 0.965	0.967; 0.947; 0.957
2	0.953; 0.936; 0.945	0.953; 0.920; 0.937	0.961; 0.936; 0.949
3	0.949; 0.951; 0.949	0.954; 0.959; 0.957	0.954; 0.959; 0.957
4	0.983; 0.932; 0.957	0.983; 0.955; 0.961	0.983; 0.962; 0.972
5	0.983; 0.924; 0.953	0.983; 0.931; 0.957	0.983; 0.947; 0.965
Avarage	0.969; 0.934; 0.951	0.968; 0.945; 0.955	0.970; 0.950; 0.960

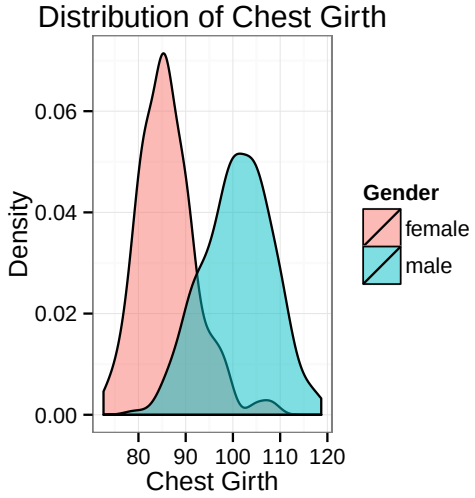
- **Inference**
  Logistic Regression $\surd$
- **Prediction**
  Ada-boosting $\surd$

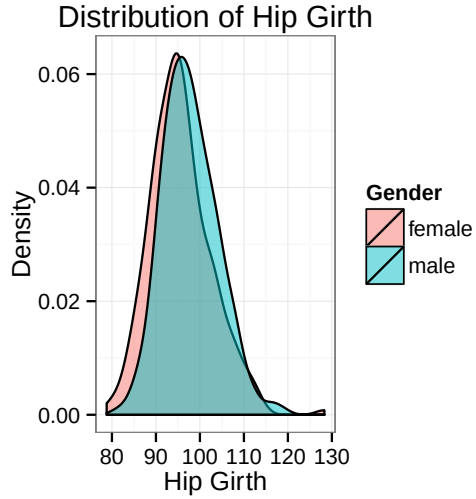
Differences between Males and Females (Liza)

- Are there significant differences in the body measurements most useful for predicting weight in males and females?
- Is one regression formula appropriate for predicting weight for both genders?
- Can we use regression trees to help explore these questions?



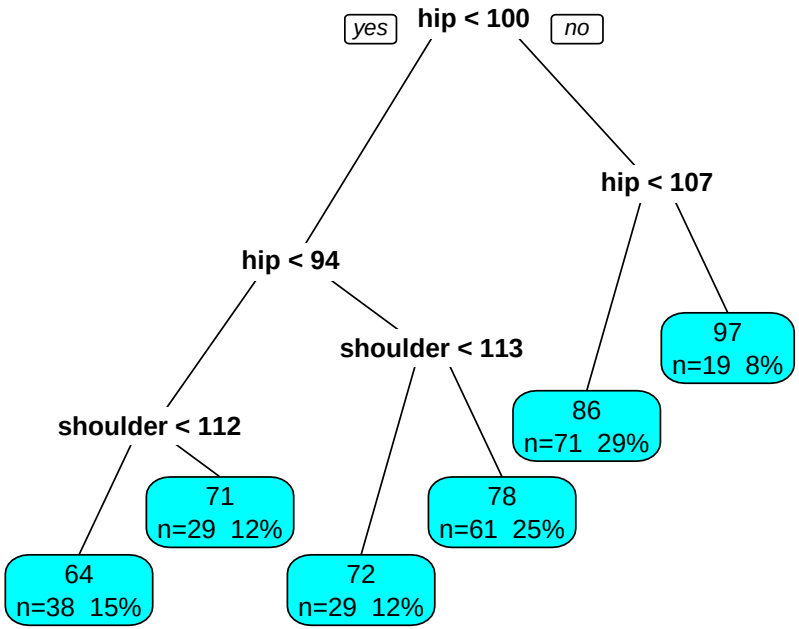




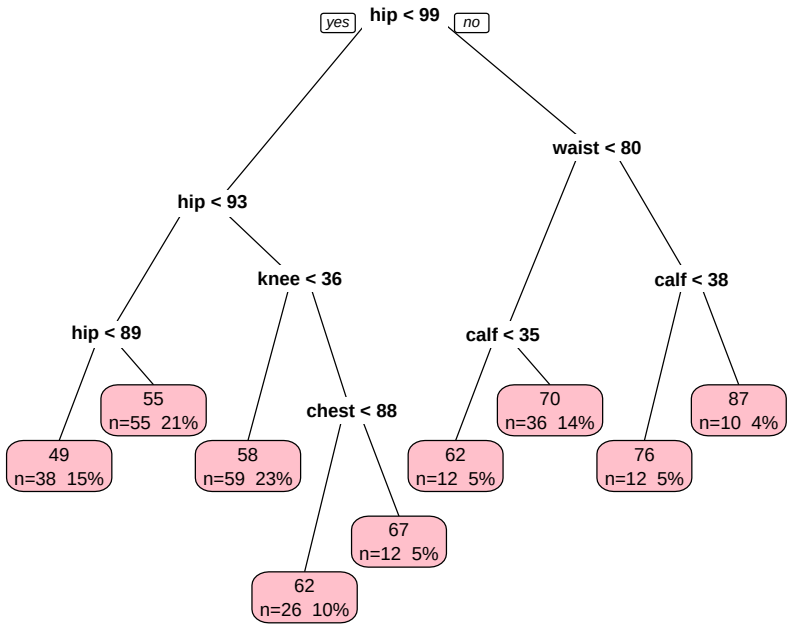


Regression Trees (Liza)

Pruned Tree, Weight (Male)



Regression Tree, Weight (Female)

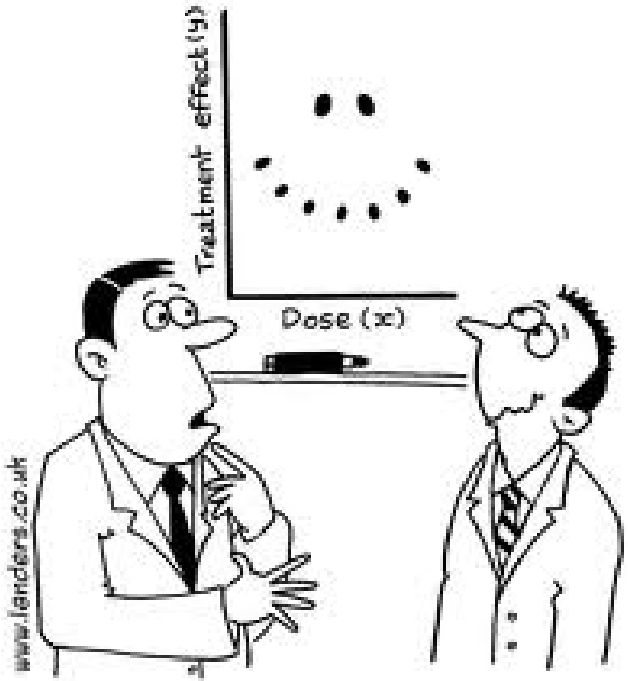


- Variables used in male tree: hip shoulder girths
- Variable used in female tree: hip, knee, chest, waist and calf girths

Conclusions (Liza)

- Regression trees are useful for exploring data and provide a useful alternative to parametric regression methods, though are not intended for making predictions.
- Results here suggest that separate models for males and females might be appropriate.
- Model fitting and selection exercises could test this hypothesis.

Group Conclusions



"It's a non-linear pattern with outliers.....but for some reason I'm very happy with the data."

What have we learned?

- Nick's Conclusion
- With model selection, a combination of selection criteria, R functions and intuition are needed to create the model of "best" fit.
- Inference choose Logistic Regression; prediction choose Ada-boosting.
- Liza's conclusion