



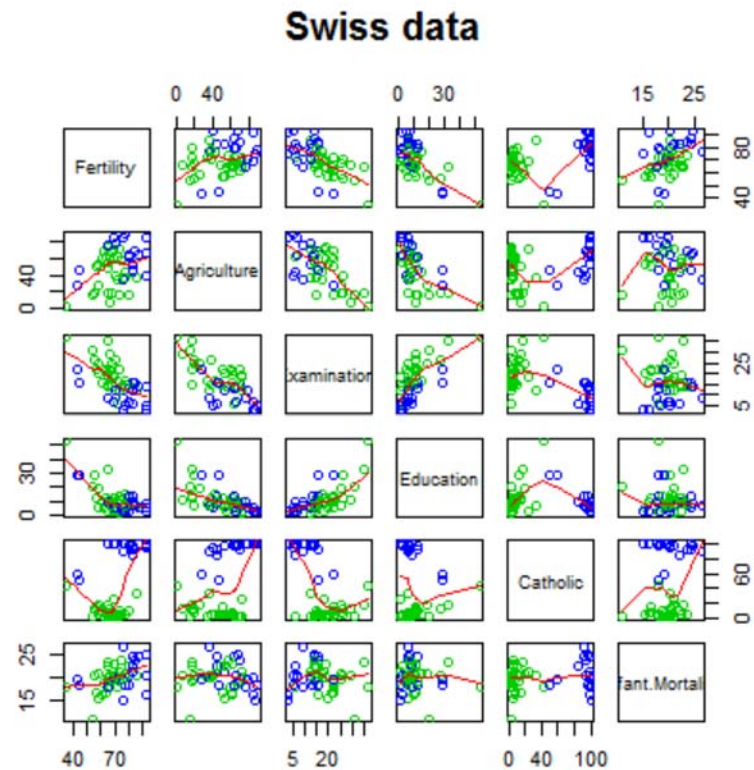
Multivariable regression examples

Regression Models

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Swiss fertility data

```
library(datasets); data(swiss); require(stats); require(graphics)
pairs(swiss, panel = panel.smooth, main = "Swiss data", col = 3 + (swiss$Catholic > 50))
```



?swiss

Description

Standardized fertility measure and socio-economic indicators for each of 47 French-speaking provinces of Switzerland at about 1888.

A data frame with 47 observations on 6 variables, each of which is in percent, i.e., in [0, 100].

- [,1] Fertility lg, 'common standardized fertility measure'
- [,2] Agriculture % of males involved in agriculture as occupation
- [,3] Examination % draftees receiving highest mark on army examination
- [,4] Education % education beyond primary school for draftees.
- [,5] Catholic % 'catholic' (as opposed to 'protestant').
- [,6] Infant.Mortality live births who live less than 1 year.

All variables but 'Fertility' give proportions of the population.

Calling `lm`

```
summary(lm(Fertility ~ . , data = swiss))
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	66.9152	10.70604	6.250	1.906e-07
Agriculture	-0.1721	0.07030	-2.448	1.873e-02
Examination	-0.2580	0.25388	-1.016	3.155e-01
Education	-0.8709	0.18303	-4.758	2.431e-05
Catholic	0.1041	0.03526	2.953	5.190e-03
Infant.Mortality	1.0770	0.38172	2.822	7.336e-03

Example interpretation

- Agriculture is expressed in percentages (0 - 100)
- Estimate is -0.1721.
- We estimate an expected 0.17 decrease in standardized fertility for every 1\% increase in percentage of males involved in agriculture in holding the remaining variables constant.
- The t-test for $H_0 : \beta_{Agri} = 0$ versus $H_a : \beta_{Agri} \neq 0$ is significant.
- Interestingly, the unadjusted estimate is

```
summary(lm(Fertility ~ Agriculture, data = swiss))$coefficients
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	60.3044	4.25126	14.185	3.216e-18
Agriculture	0.1942	0.07671	2.532	1.492e-02

How can adjustment reverse the sign of an effect? Let's try a simulation.

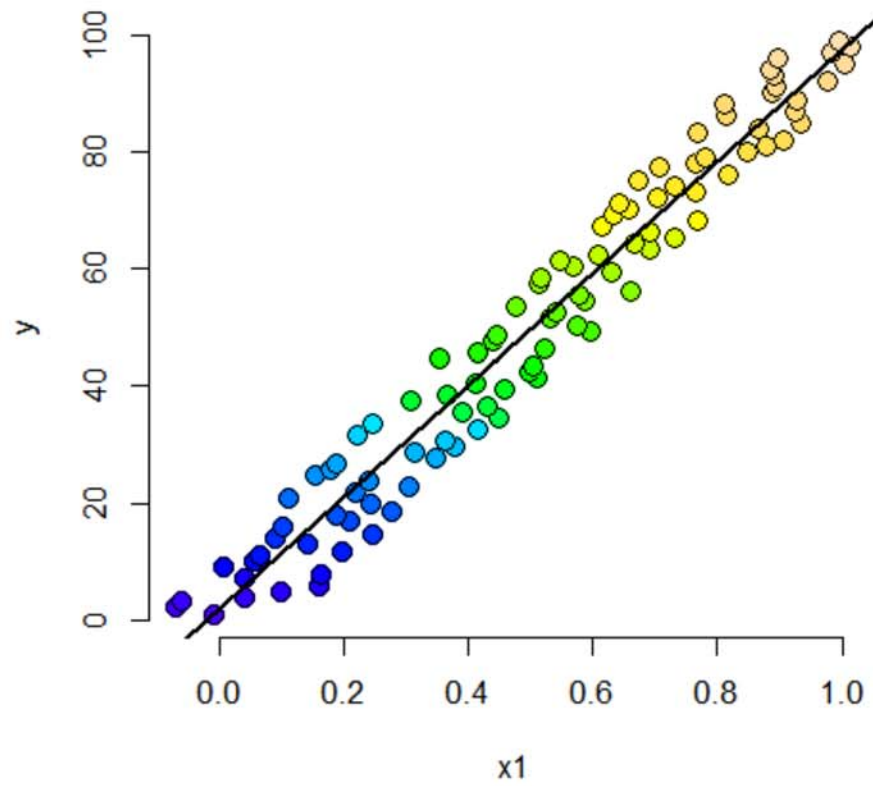
```
n <- 100; x2 <- 1 : n; x1 <- .01 * x2 + runif(n, -.1, .1); y = -x1 + x2 + rnorm(n, sd = .01)
summary(lm(y ~ x1))$coef
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.618	1.200	1.349	1.806e-01
x1	95.854	2.058	46.579	1.153e-68

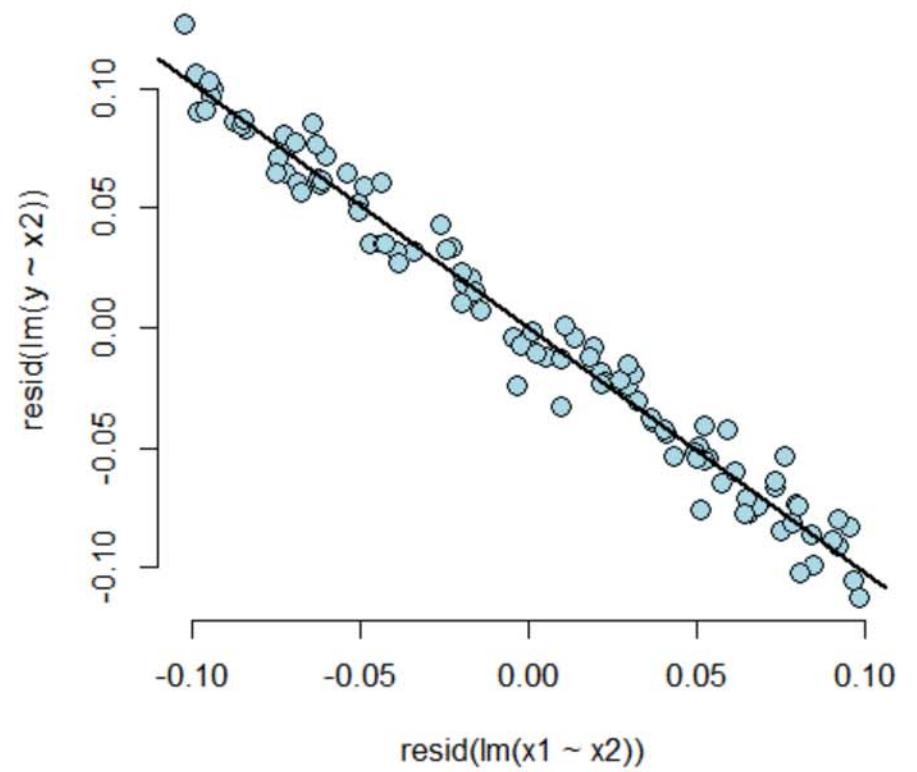
```
summary(lm(y ~ x1 + x2))$coef
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.0003683	0.0020141	0.1829	8.553e-01
x1	-1.0215256	0.0166372	-61.4001	1.922e-79
x2	1.0001909	0.0001681	5950.1818	1.369e-271

Unadjusted, color is X2



Adjusted



Back to this data set

- The sign reverses itself with the inclusion of Examination and Education, but of which are negatively correlated with Agriculture.
- The percent of males in the province working in agriculture is negatively related to educational attainment (correlation of -0.6395) and Education and Examination (correlation of 0.6984) are obviously measuring similar things.
 - Is the positive marginal an artifact for not having accounted for, say, Education level? (Education does have a stronger effect, by the way.)
- At the minimum, anyone claiming that provinces that are more agricultural have higher fertility rates would immediately be open to criticism.

What if we include an unnecessary variable?

z adds no new linear information, since it's a linear combination of variables already included. R just drops terms that are linear combinations of other terms.

```
z <- swiss$Agriculture + swiss$Education  
lm(Fertility ~ . + z, data = swiss)
```

Call:

```
lm(formula = Fertility ~ . + z, data = swiss)
```

Coefficients:

(Intercept)	Agriculture	Examination	Education	Catholic
66.915	-0.172	-0.258	-0.871	0.104
Infant.Mortality	z			
1.077	NA			

Dummy variables are smart

- Consider the linear model

$$Y_i = \beta_0 + X_{i1}\beta_1 + \epsilon_i$$

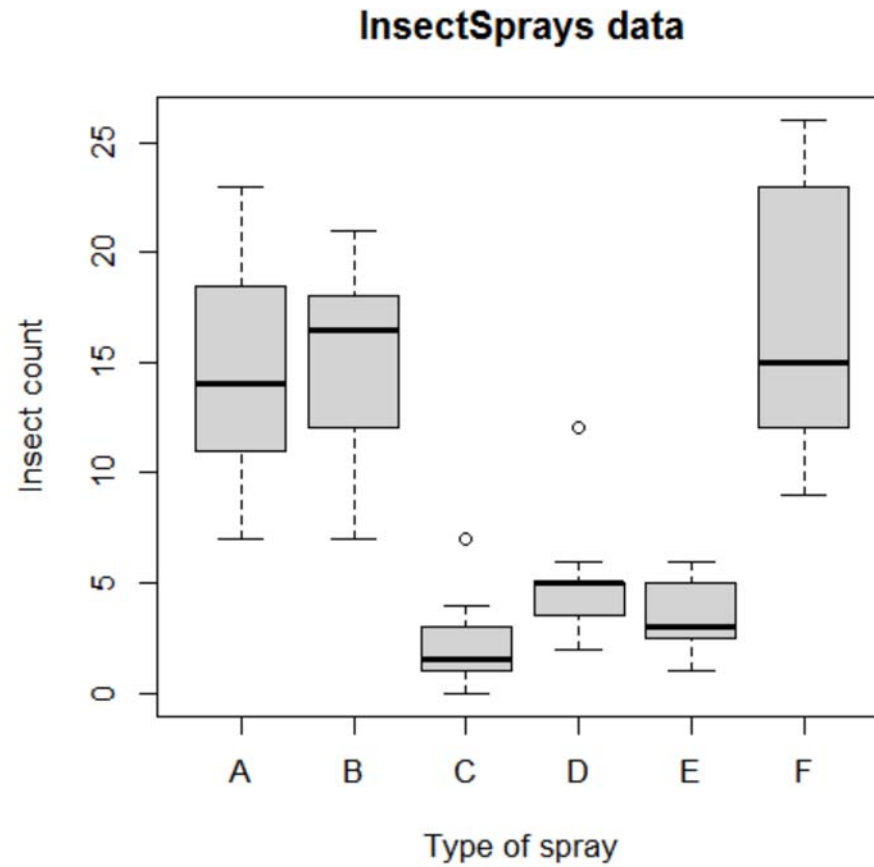
where each X_{i1} is binary so that it is a 1 if measurement i is in a group and 0 otherwise. (Treated versus not in a clinical trial, for example.)

- Then for people in the group $E[Y_i] = \beta_0 + \beta_1$
- And for people not in the group $E[Y_i] = \beta_0$
- The LS fits work out to be $\hat{\beta}_0 + \hat{\beta}_1$ is the mean for those in the group and $\hat{\beta}_0$ is the mean for those not in the group.
- β_1 is interpreted as the increase or decrease in the mean comparing those in the group to those not.
- Note including a binary variable that is 1 for those not in the group would be redundant. It would create three parameters to describe two means.

More than 2 levels

- Consider a multilevel factor level. For didactic reasons, let's say a three level factor (example, US political party affiliation: Republican, Democrat, Independent)
- $Y_i = \beta_0 + X_{i1}\beta_1 + X_{i2}\beta_2 + \epsilon_i$.
- X_{i1} is 1 for Republicans and 0 otherwise.
- X_{i2} is 1 for Democrats and 0 otherwise.
- If i is Republican $E[Y_i] = \beta_0 + \beta_1$
- If i is Democrat $E[Y_i] = \beta_0 + \beta_2$.
- If i is Independent $E[Y_i] = \beta_0$.
- β_1 compares Republicans to Independents.
- β_2 compares Democrats to Independents.
- $\beta_1 - \beta_2$ compares Republicans to Democrats.
- (Choice of reference category changes the interpretation.)

Insect Sprays



Linear model fit, group A is the reference

```
summary(lm(count ~ spray, data = InsectSprays))$coef
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	14.5000	1.132	12.8074	1.471e-19
sprayB	0.8333	1.601	0.5205	6.045e-01
sprayC	-12.4167	1.601	-7.7550	7.267e-11
sprayD	-9.5833	1.601	-5.9854	9.817e-08
sprayE	-11.0000	1.601	-6.8702	2.754e-09
sprayF	2.1667	1.601	1.3532	1.806e-01

Hard coding the dummy variables

```
summary(lm(count ~  
          I(1 * (spray == 'B')) + I(1 * (spray == 'C')) +  
          I(1 * (spray == 'D')) + I(1 * (spray == 'E')) +  
          I(1 * (spray == 'F'))  
        , data = InsectSprays))$coef
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	14.5000	1.132	12.8074	1.471e-19
I(1 * (spray == "B"))	0.8333	1.601	0.5205	6.045e-01
I(1 * (spray == "C"))	-12.4167	1.601	-7.7550	7.267e-11
I(1 * (spray == "D"))	-9.5833	1.601	-5.9854	9.817e-08
I(1 * (spray == "E"))	-11.0000	1.601	-6.8702	2.754e-09
I(1 * (spray == "F"))	2.1667	1.601	1.3532	1.806e-01

What if we include all 6?

```
lm(count ~  
  I(1 * (spray == 'B')) + I(1 * (spray == 'C')) +  
  I(1 * (spray == 'D')) + I(1 * (spray == 'E')) +  
  I(1 * (spray == 'F')) + I(1 * (spray == 'A')), data = InsectSprays)
```

Call:

```
lm(formula = count ~ I(1 * (spray == "B")) + I(1 * (spray ==  
  "C")) + I(1 * (spray == "D")) + I(1 * (spray == "E")) + I(1 *  
  (spray == "F")) + I(1 * (spray == "A")), data = InsectSprays)
```

Coefficients:

(Intercept)	I(1 * (spray == "B"))	I(1 * (spray == "C"))	I(1 * (spray == "D"))
14.500	0.833	-12.417	-9.583
I(1 * (spray == "E"))	I(1 * (spray == "F"))	I(1 * (spray == "A"))	
-11.000	2.167	NA	

What if we omit the intercept?

```
summary(lm(count ~ spray - 1, data = InsectSprays))$coef
```

	Estimate	Std. Error	t value	Pr(> t)
sprayA	14.500	1.132	12.807	1.471e-19
sprayB	15.333	1.132	13.543	1.002e-20
sprayC	2.083	1.132	1.840	7.024e-02
sprayD	4.917	1.132	4.343	4.953e-05
sprayE	3.500	1.132	3.091	2.917e-03
sprayF	16.667	1.132	14.721	1.573e-22

```
unique(ave(InsectSprays$count, InsectSprays$spray))
```

```
[1] 14.500 15.333 2.083 4.917 3.500 16.667
```


Summary

- If we treat Spray as a factor, R includes an intercept and omits the alphabetically first level of the factor.
 - All t-tests are for comparisons of Sprays versus Spray A.
 - Empirical mean for A is the intercept.
 - Other group means are the intercept plus their coefficient.
- If we omit an intercept, then it includes terms for all levels of the factor.
 - Group means are the coefficients.
 - Tests are tests of whether the groups are different than zero. (Are the expected counts zero for that spray.)
- If we want comparisons between, Spray B and C, say we could refit the model with C (or B) as the reference level.

Reordering the levels

```
spray2 <- relevel(InsectSprays$spray, "C")  
summary(lm(count ~ spray2, data = InsectSprays))$coef
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.083	1.132	1.8401	7.024e-02
spray2A	12.417	1.601	7.7550	7.267e-11
spray2B	13.250	1.601	8.2755	8.510e-12
spray2D	2.833	1.601	1.7696	8.141e-02
spray2E	1.417	1.601	0.8848	3.795e-01
spray2F	14.583	1.601	9.1083	2.794e-13

Doing it manually

Equivalently

$$\text{Var}(\hat{\beta}_B - \hat{\beta}_C) = \text{Var}(\hat{\beta}_B) + \text{Var}(\hat{\beta}_C) - 2\text{Cov}(\hat{\beta}_B, \hat{\beta}_C)$$

```
fit <- lm(count ~ spray, data = InsectSprays) #A is ref
bbmbc <- coef(fit)[2] - coef(fit)[3] #B - C
temp <- summary(fit)
se <- temp$sigma * sqrt(temp$cov.unscaled[2, 2] + temp$cov.unscaled[3, 3] - 2 * temp$cov.unscaled[2, 3])
t <- (bbmbc) / se
p <- pt(-abs(t), df = fit$df)
out <- c(bbmbc, se, t, p)
names(out) <- c("B - C", "SE", "T", "P")
round(out, 3)
```

B - C	SE	T	P
13.250	1.601	8.276	0.000

Other thoughts on this data

- Counts are bounded from below by 0, violates the assumption of normality of the errors.
 - Also there are counts near zero, so both the actual assumption and the intent of the assumption are violated.
- Variance does not appear to be constant.
- Perhaps taking logs of the counts would help.
 - There are 0 counts, so maybe $\log(\text{Count} + 1)$
- Also, we'll cover Poisson GLMs for fitting count data.

Example - Millenium Development Goal 1

http://www.un.org/millenniumgoals/pdf/MDG_FS_1_EN.pdf

http://apps.who.int/gho/athena/data/GHO/WHOSIS_000008.csv?profile=text&filter=COUNTRY;;SEX:

WHO childhood hunger data

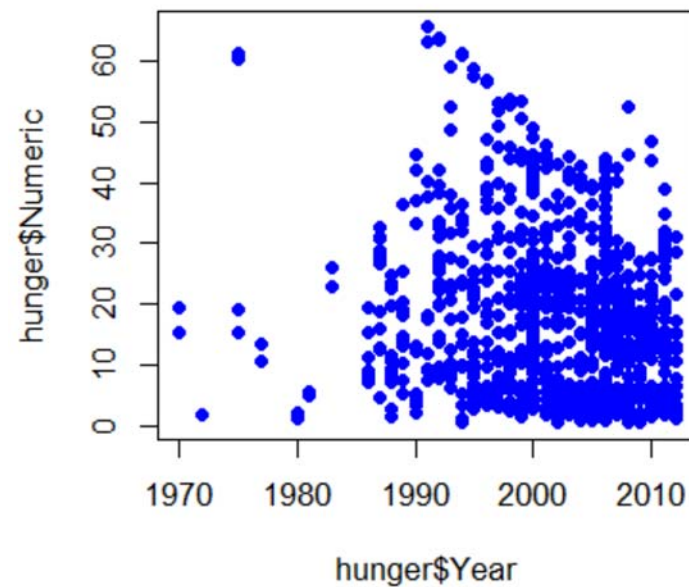
```
#download.file("http://apps.who.int/gho/athena/data/GHO/WHOSIS_000008.csv?profile=text&filter=COUNT")
hunger <- read.csv("hunger.csv")
hunger <- hunger[hunger$Sex!="Both sexes",]
head(hunger)
```

	Indicator	Data.Source	PUBLISH.STATES	Year	WHO.region
1	Children aged <5 years underweight (%)	NLIS_310044	Published	1986	Africa
2	Children aged <5 years underweight (%)	NLIS_310233	Published	1990	Americas
3	Children aged <5 years underweight (%)	NLIS_312902	Published	2005	Americas
5	Children aged <5 years underweight (%)	NLIS_312522	Published	2002	Eastern Mediterranean
6	Children aged <5 years underweight (%)	NLIS_312955	Published	2008	Africa
8	Children aged <5 years underweight (%)	NLIS_312963	Published	2008	Africa

	Country	Sex	Display.Value	Numeric	Low	High	Comments
1	Senegal	Male	19.3	19.3	NA	NA	NA
2	Paraguay	Male	2.2	2.2	NA	NA	NA
3	Nicaragua	Male	5.3	5.3	NA	NA	NA
5	Jordan	Female	3.2	3.2	NA	NA	NA
6	Guinea-Bissau	Female	17.0	17.0	NA	NA	NA
8	Ghana	Male	15.7	15.7	NA	NA	NA

Plot percent hungry versus time

```
lm1 <- lm(hunger$Numeric ~ hunger$Year)
plot(hunger$Year, hunger$Numeric, pch=19, col="blue")
```



Remember the linear model

$$Hu_i = b_0 + b_1 Y_i + e_i$$

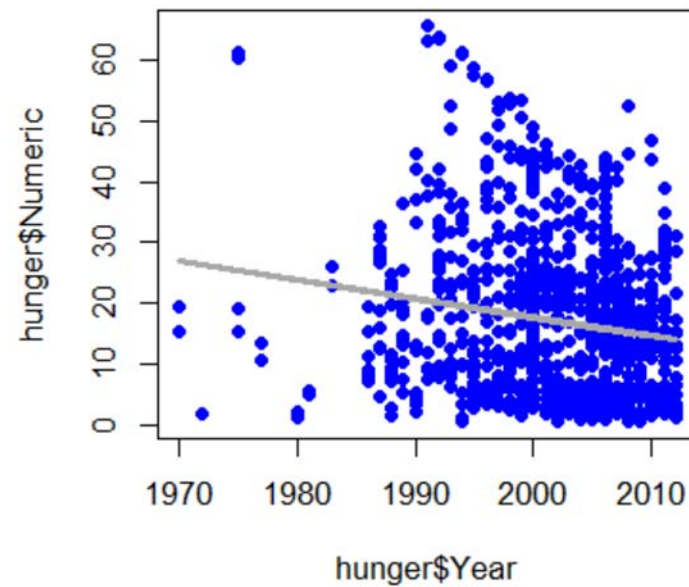
b_0 = percent hungry at Year 0

b_1 = decrease in percent hungry per year

e_i = everything we didn't measure

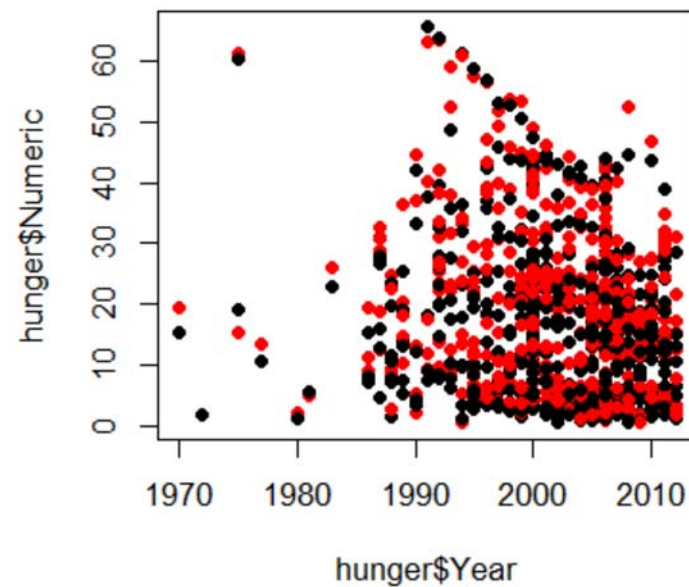
Add the linear model

```
lm1 <- lm(hunger$Numeric ~ hunger$Year)
plot(hunger$Year, hunger$Numeric, pch=19, col="blue")
lines(hunger$Year, lm1$fitted, lwd=3, col="darkgrey")
```



Color by male/female

```
plot(hunger$Year,hunger$Numeric,pch=19)  
points(hunger$Year,hunger$Numeric,pch=19,col=((hunger$Sex=="Male")*1+1))
```



Now two lines

$$HuF_i = bf_0 + bf_1 YF_i + ef_i$$

bf_0 = percent of girls hungry at Year 0

bf_1 = decrease in percent of girls hungry per year

ef_i = everything we didn't measure

$$HuM_i = bm_0 + bm_1 YM_i + em_i$$

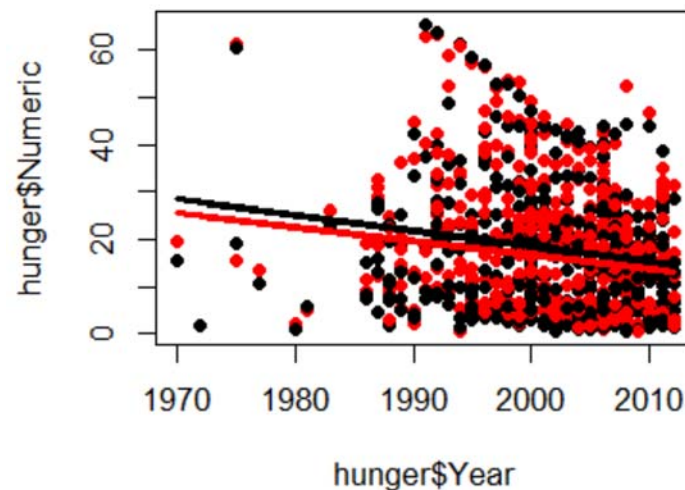
bm_0 = percent of boys hungry at Year 0

bm_1 = decrease in percent of boys hungry per year

em_i = everything we didn't measure

Color by male/female

```
lmM <- lm(hunger$Numeric[hunger$Sex=="Male"] ~ hunger$Year[hunger$Sex=="Male"])\nlmF <- lm(hunger$Numeric[hunger$Sex=="Female"] ~ hunger$Year[hunger$Sex=="Female"])\nplot(hunger$Year,hunger$Numeric,pch=19)\npoints(hunger$Year,hunger$Numeric,pch=19,col=((hunger$Sex=="Male")*1+1))\nlines(hunger$Year[hunger$Sex=="Male"],lmM$fitted,col="black",lwd=3)\nlines(hunger$Year[hunger$Sex=="Female"],lmF$fitted,col="red",lwd=3)
```



Two lines, same slope

$$Hu_i = b_0 + b_1 1(\text{Sex}_i = \text{Male}) + b_2 Y_i + e_i^*$$

b_0 - percent hungry at year zero for females

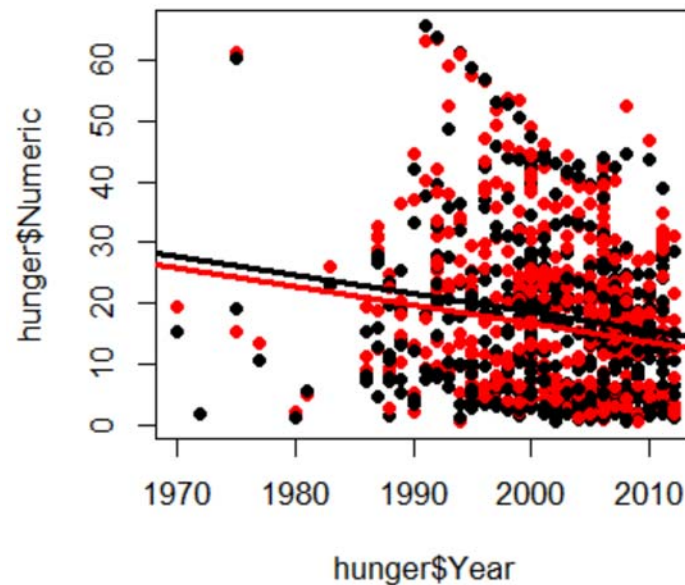
$b_0 + b_1$ - percent hungry at year zero for males

b_2 - change in percent hungry (for either males or females) in one year

e_i^* - everything we didn't measure

Two lines, same slope in R

```
lmBoth <- lm(hunger$Numeric ~ hunger$Year + hunger$Sex)
plot(hunger$Year,hunger$Numeric,pch=19)
points(hunger$Year,hunger$Numeric,pch=19,col=((hunger$Sex=="Male")*1+1))
abline(c(lmBoth$coeff[1],lmBoth$coeff[2]),col="red",lwd=3)
abline(c(lmBoth$coeff[1] + lmBoth$coeff[3],lmBoth$coeff[2]),col="black",lwd=3)
```



Two lines, different slopes (interactions)

$$Hu_i = b_0 + b_1 1(\text{Sex}_i = \text{"Male"}) + b_2 Y_i + b_3 1(\text{Sex}_i = \text{"Male"}) \times Y_i + e_i^+$$

b_0 - percent hungry at year zero for females

$b_0 + b_1$ - percent hungry at year zero for males

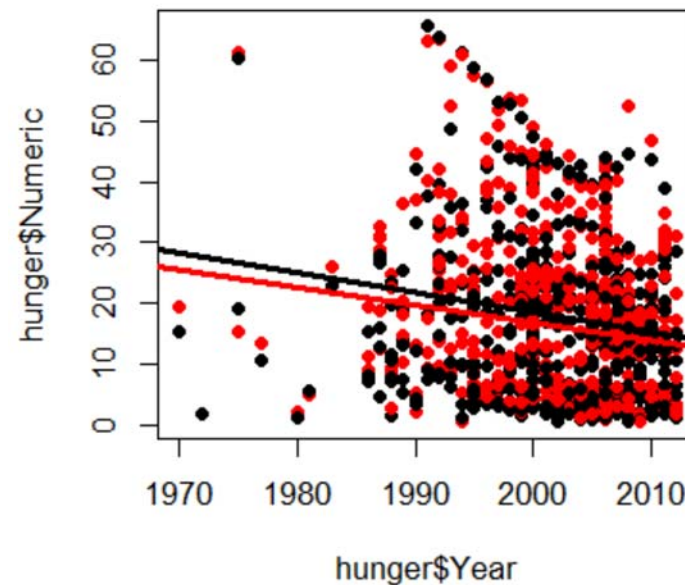
b_2 - change in percent hungry (females) in one year

$b_2 + b_3$ - change in percent hungry (males) in one year

e_i^+ - everything we didn't measure

Two lines, different slopes in R

```
lmBoth <- lm(hunger$Numeric ~ hunger$Year + hunger$Sex + hunger$Sex*hunger$Year)
plot(hunger$Year,hunger$Numeric,pch=19)
points(hunger$Year,hunger$Numeric,pch=19,col=((hunger$Sex=="Male")*1+1))
abline(c(lmBoth$coeff[1],lmBoth$coeff[2]),col="red",lwd=3)
abline(c(lmBoth$coeff[1] + lmBoth$coeff[3],lmBoth$coeff[2] +lmBoth$coeff[4]),col="black",lwd=3)
```



Two lines, different slopes in R

```
summary(lmBoth)
```

Call:

```
lm(formula = hunger$Numeric ~ hunger$Year + hunger$Sex + hunger$Sex *  
    hunger$Year)
```

Residuals:

Min	1Q	Median	3Q	Max
-25.91	-11.25	-1.85	7.09	46.15

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	603.5058	171.0552	3.53	0.00044	***
hunger\$Year	-0.2934	0.0855	-3.43	0.00062	***
hunger\$SexMale	61.9477	241.9086	0.26	0.79795	
hunger\$Year:hunger\$SexMale	-0.0300	0.1209	-0.25	0.80402	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 13.2 on 944 degrees of freedom

Multiple R-squared: 0.0318, Adjusted R-squared: 0.0287

F-statistic: 10.3 on 3 and 944 DF, p-value: 1.06e-06

Interpreting a continuous interaction

$$E[Y_i | X_{1i} = x_1, X_{2i} = x_2] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2$$

Holding X_2 constant we have

$$E[Y_i | X_{1i} = x_1 + 1, X_{2i} = x_2] - E[Y_i | X_{1i} = x_1, X_{2i} = x_2] = \beta_1 + \beta_3 x_2$$

And thus the expected change in Y per unit change in X_1 holding all else constant is not constant. β_1 is the slope when $x_2 = 0$. Note further that:

$$\begin{aligned} & E[Y_i | X_{1i} = x_1 + 1, X_{2i} = x_2 + 1] - E[Y_i | X_{1i} = x_1, X_{2i} = x_2 + 1] \\ & - E[Y_i | X_{1i} = x_1 + 1, X_{2i} = x_2] - E[Y_i | X_{1i} = x_1, X_{2i} = x_2] \\ & = \beta_3 \end{aligned}$$

Thus, β_3 is the change in the expected change in Y per unit change in X_1 , per unit change in X_2 .

Or, the change in the slope relating X_1 and Y per unit change in X_2 .

Example

$$Hu_i = b_0 + b_1 In_i + b_2 Y_i + b_3 In_i \times Y_i + e_i^+$$

b_0 - percent hungry at year zero for children with whose parents have no income

b_1 - change in percent hungry for each dollar of income in year zero

b_2 - change in percent hungry in one year for children whose parents have no income

b_3 - increased change in percent hungry by year for each dollar of income - e.g. if income is \$10,000, then change in percent hungry in one year will be

$$b_2 + 1e4 \times b_3$$

e_i^+ - everything we didn't measure

Lot's of care/caution needed!