

# Multivariable regression examples

## Regression Models

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### Data set for discussion

```
require(datasets); data(swiss); ?swiss
```

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

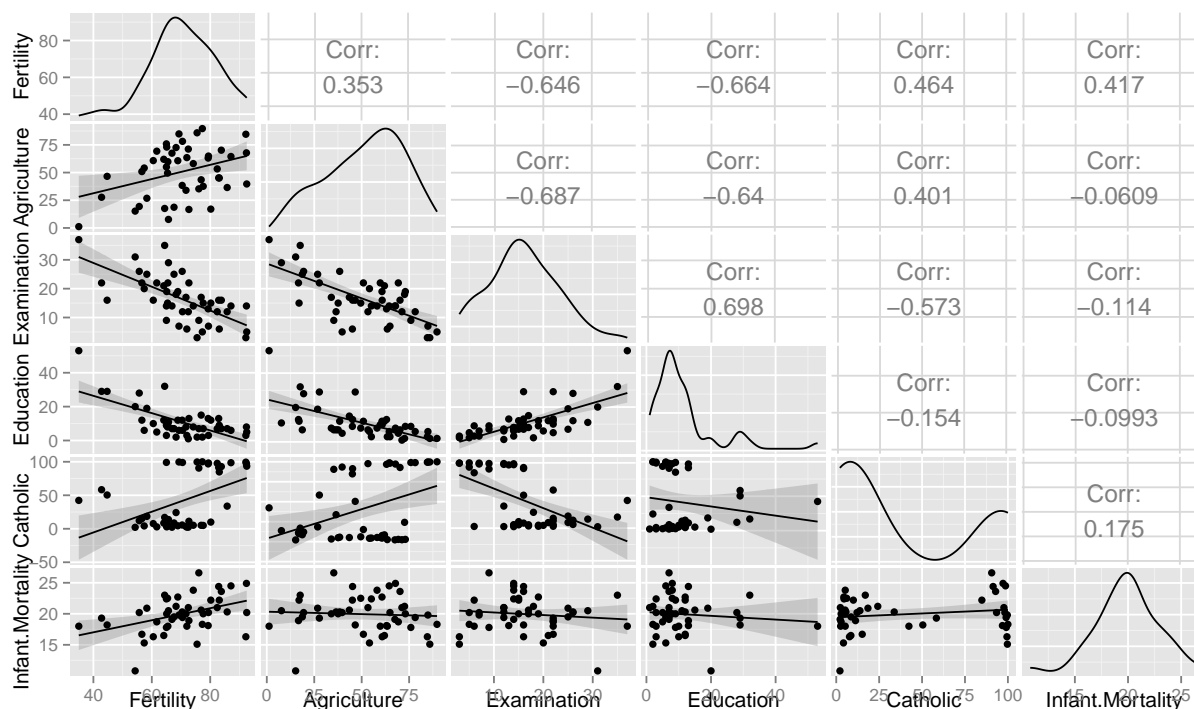
A data frame with 47 observations on 6 variables, each of which is in percent, i.e., in  $[0, 100]$ .

- [1] Fertility a 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.

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```
## Loading required package: GGally  
## Loading required package: ggplot2
```



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## Calling lm

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

```
##              Estimate Std. Error  t value    Pr(>|t|)
## (Intercept)   66.9151817 10.70603759   6.250229 1.906051e-07
## Agriculture   -0.1721140  0.07030392  -2.448142 1.872715e-02
## Examination   -0.2580082  0.25387820  -1.016268 3.154617e-01
## Education     -0.8709401  0.18302860  -4.758492 2.430605e-05
## Catholic       0.1041153  0.03525785   2.952969 5.190079e-03
## Infant.Mortality 1.0770481  0.38171965   2.821568 7.335715e-03
```

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## Example interpretation

- Agriculture is expressed in percentages (0 - 100)
- Estimate is -0.1721.
- Our models estimates 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)  60.3043752  4.25125562 14.185074 3.216304e-18
## Agriculture   0.1942017  0.07671176   2.531577 1.491720e-02
```

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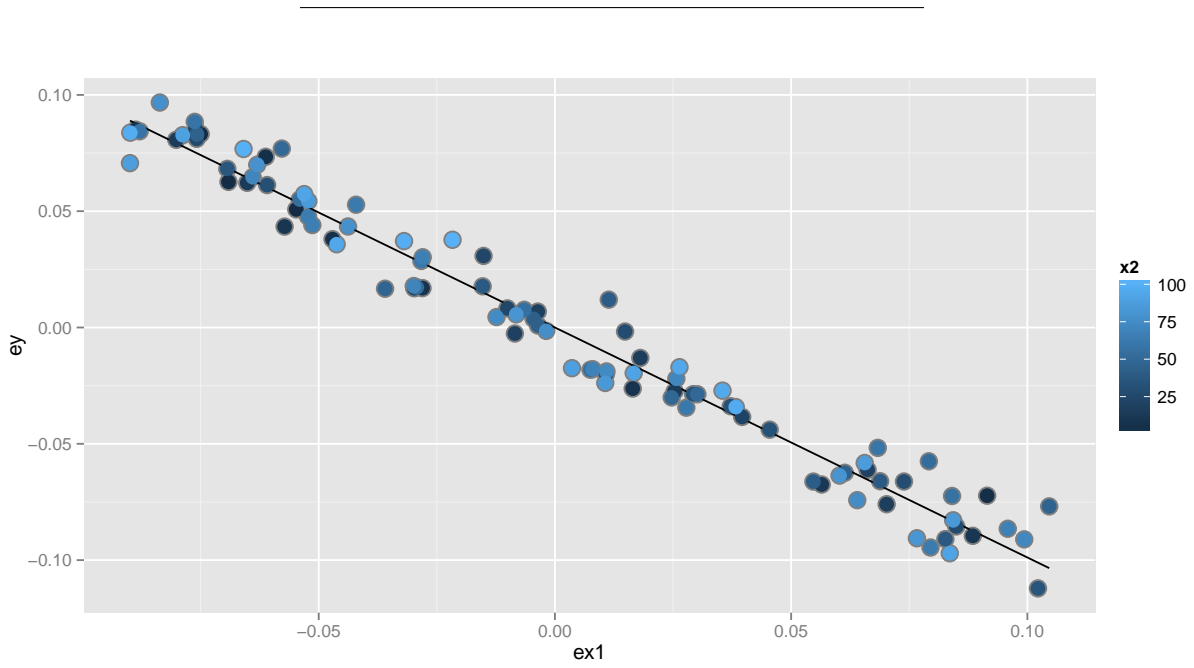
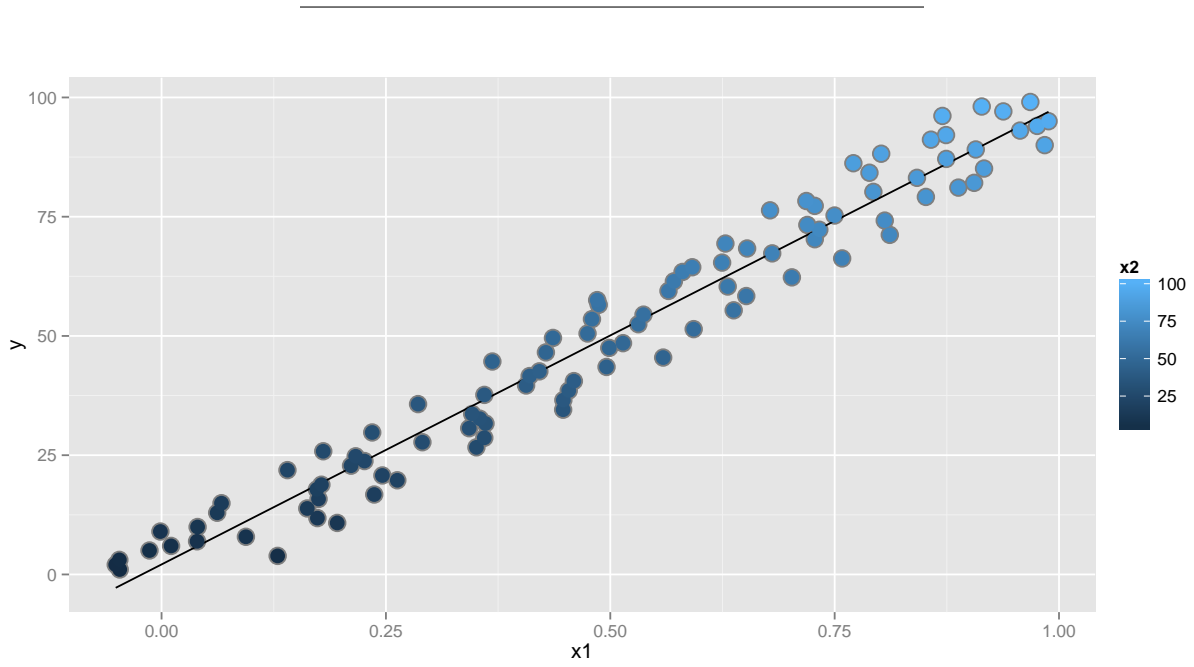
## How can adjustment reverse the sign of an effect? Let's try a simulation.

```
set.seed(3793)
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)   2.100344   1.128227   1.861634 6.565164e-02
## x1            96.012028   1.951963  49.187423 6.871677e-71
```

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

```
##              Estimate Std. Error  t value    Pr(>|t|)
## (Intercept) -0.001781856 0.0019811152  -0.8994205 3.706561e-01
## x1          -0.988683346 0.0172412013 -57.3442261 1.219580e-76
## x2           0.999938050 0.0001743071 5736.6470230 4.742028e-270
```



## 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
##      66.9152      -0.1721      -0.2580      -0.8709
##      Catholic Infant.Mortality      z
##      0.1041      1.0770      NA
```

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## Dummy variables are smart

- Consider the linear model

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

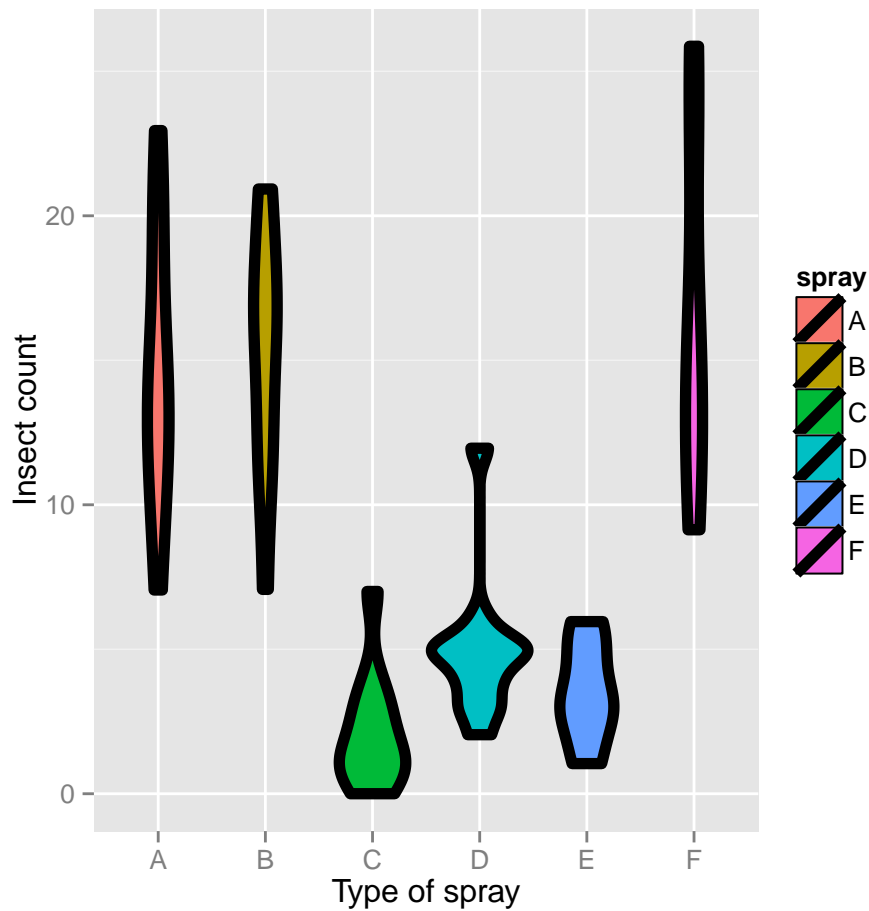
where each  $X_{i1}$  is binary so that it is a 1 if measurement  $i$  is in a group and 0 otherwise. (Treated versus not in a clinical trial, for example.)

- 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.
  - $\beta_1$  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  $E[Y_i] = \beta_0$ .
  - $\beta_1$  compares Republicans to Independents.
  - $\beta_2$  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)	14.5000000	1.132156	12.8074279	1.470512e-19
## sprayB	0.8333333	1.601110	0.5204724	6.044761e-01
## sprayC	-12.4166667	1.601110	-7.7550382	7.266893e-11
## sprayD	-9.5833333	1.601110	-5.9854322	9.816910e-08
## sprayE	-11.0000000	1.601110	-6.8702352	2.753922e-09
## sprayF	2.1666667	1.601110	1.3532281	1.805998e-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)	14.5000000	1.132156	12.8074279	1.470512e-19
##	I(1 * (spray == "B"))	0.8333333	1.601110	0.5204724	6.044761e-01
##	I(1 * (spray == "C"))	-12.4166667	1.601110	-7.7550382	7.266893e-11
##	I(1 * (spray == "D"))	-9.5833333	1.601110	-5.9854322	9.816910e-08
##	I(1 * (spray == "E"))	-11.0000000	1.601110	-6.8702352	2.753922e-09
##	I(1 * (spray == "F"))	2.1666667	1.601110	1.3532281	1.805998e-01

---

## What if we include all 6?

```
summary(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))$coef
```

##		Estimate	Std. Error	t value	Pr(> t )
##	(Intercept)	14.5000000	1.132156	12.8074279	1.470512e-19
##	I(1 * (spray == "B"))	0.8333333	1.601110	0.5204724	6.044761e-01
##	I(1 * (spray == "C"))	-12.4166667	1.601110	-7.7550382	7.266893e-11
##	I(1 * (spray == "D"))	-9.5833333	1.601110	-5.9854322	9.816910e-08
##	I(1 * (spray == "E"))	-11.0000000	1.601110	-6.8702352	2.753922e-09
##	I(1 * (spray == "F"))	2.1666667	1.601110	1.3532281	1.805998e-01

---

## What if we omit the intercept?

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

##		Estimate	Std. Error	t value	Pr(> t )
##	sprayA	14.500000	1.132156	12.807428	1.470512e-19
##	sprayB	15.333333	1.132156	13.543487	1.001994e-20
##	sprayC	2.083333	1.132156	1.840148	7.024334e-02
##	sprayD	4.916667	1.132156	4.342749	4.953047e-05
##	sprayE	3.500000	1.132156	3.091448	2.916794e-03
##	sprayF	16.666667	1.132156	14.721181	1.573471e-22

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
##
## The following object is masked from 'package:GGally':
##
##   nasa
##
## The following objects are masked from 'package:stats':
##
##   filter, lag
##
## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union
```

```
summarise(group_by(InsectSprays, spray), mn = mean(count))
```

```
## Source: local data frame [6 x 2]
##
##   spray      mn
##   (fctr)    (dbl)
## 1      A 14.500000
## 2      B 15.333333
## 3      C  2.083333
## 4      D  4.916667
## 5      E  3.500000
## 6      F 16.666667
```

## 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.

## 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.
- 

## Recall the swiss data set

```
library(datasets); data(swiss)
head(swiss)
```

```
##           Fertility Agriculture Examination Education Catholic
## Courtelary      80.2         17.0           15          12      9.96
## Delemont        83.1         45.1            6           9     84.84
## Franches-Mnt    92.5         39.7            5           5     93.40
## Moutier         85.8         36.5           12           7     33.77
## Neuveville      76.9         43.5           17          15      5.16
## Porrentruy      76.1         35.3            9           7     90.57
##
## Infant.Mortality
## Courtelary                22.2
## Delemont                  22.2
## Franches-Mnt              20.2
## Moutier                   20.3
## Neuveville                20.6
## Porrentruy                26.6
```

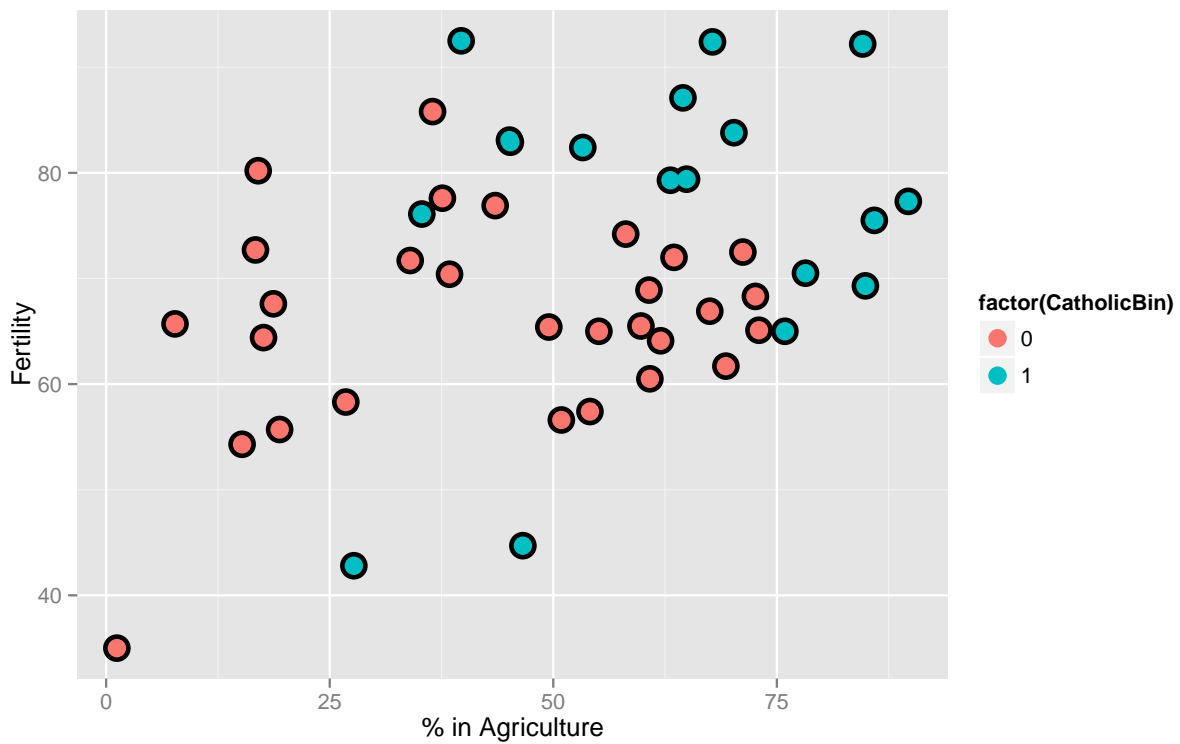
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## Create a binary variable

```
library(dplyr);  
swiss = mutate(swiss, CatholicBin = 1 * (Catholic > 50))
```

## Plot the data



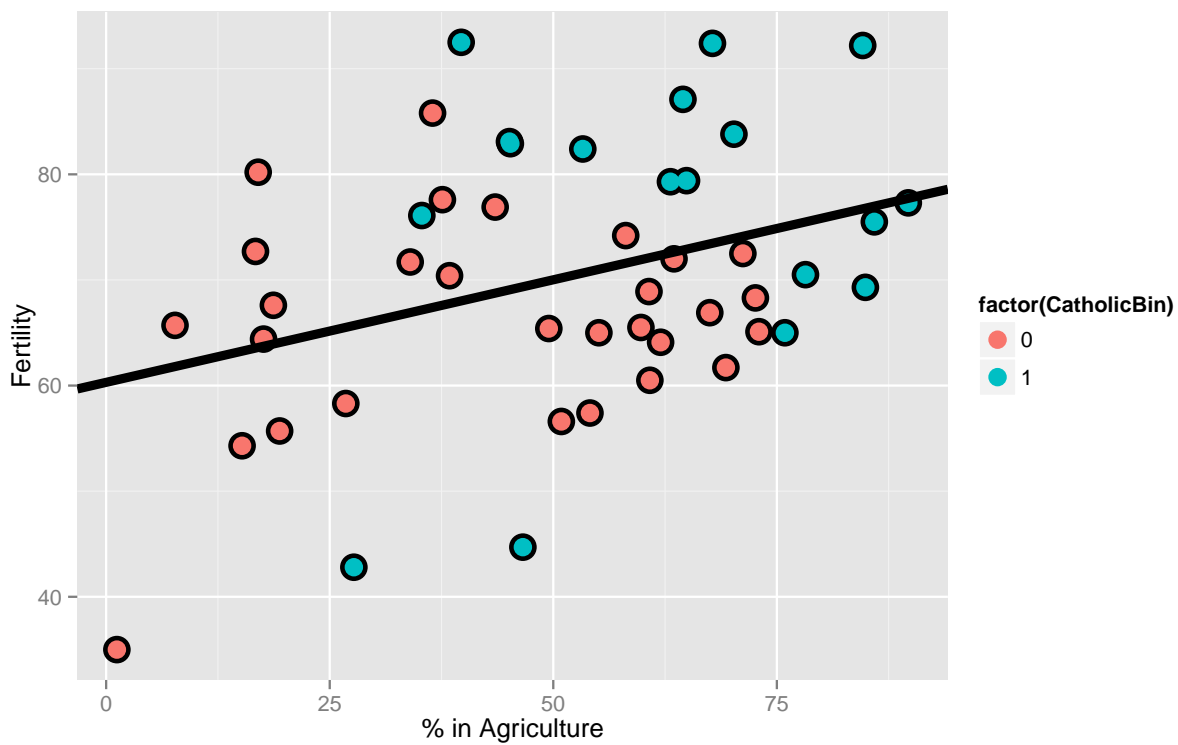
## No effect of religion

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

```
##           Estimate Std. Error  t value    Pr(>|t|)
## (Intercept) 60.3043752  4.25125562 14.185074 3.216304e-18
## Agriculture  0.1942017  0.07671176  2.531577 1.491720e-02
```

---

## The associated fitted line



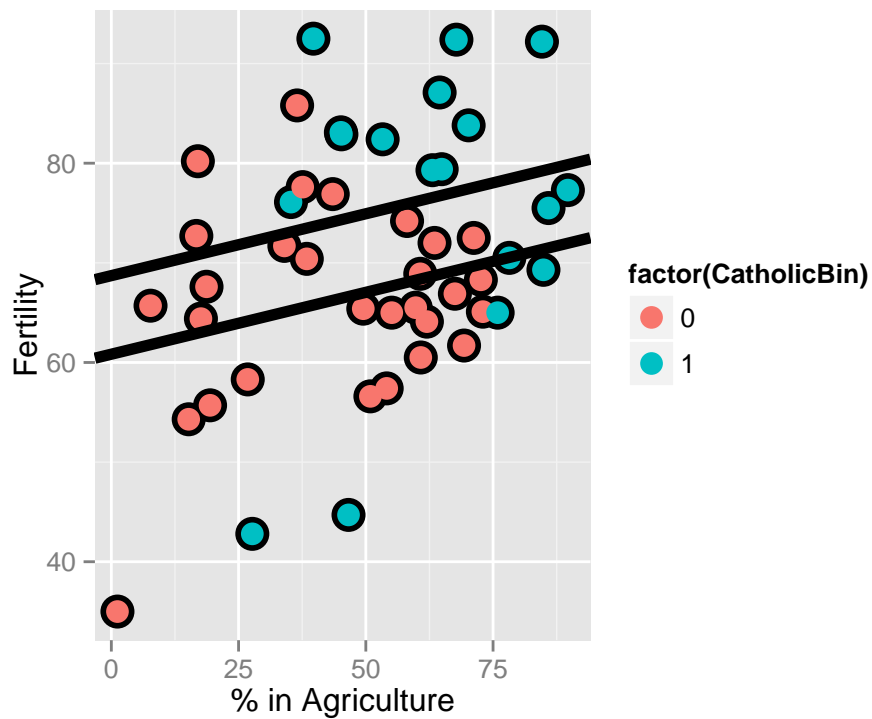
## Parallel lines

```
summary(lm(Fertility ~ Agriculture + factor(CatholicBin), data = swiss))$coef
```

##	Estimate	Std. Error	t value	Pr(> t )
## (Intercept)	60.8322366	4.1058630	14.815944	1.032493e-18
## Agriculture	0.1241776	0.0810977	1.531210	1.328763e-01
## factor(CatholicBin)1	7.8843292	3.7483622	2.103406	4.118221e-02

---

## Fitted lines



## Lines with different slopes and intercepts

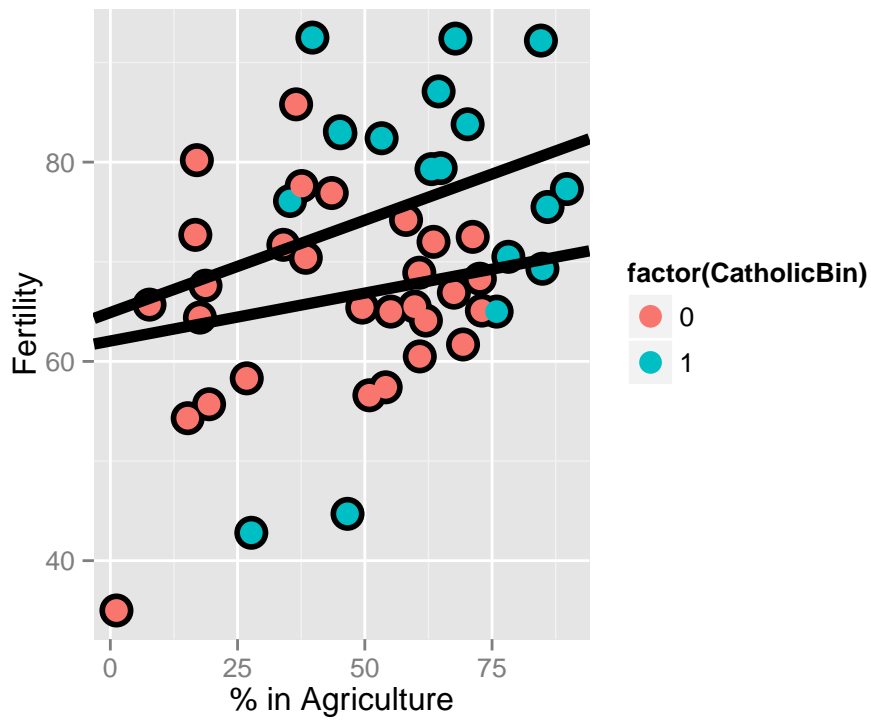
```
summary(lm(Fertility ~ Agriculture * factor(CatholicBin), data = swiss))$coef
```

##	Estimate	Std. Error	t value
## (Intercept)	62.04993019	4.78915566	12.9563402
## Agriculture	0.09611572	0.09881204	0.9727127
## factor(CatholicBin)1	2.85770359	10.62644275	0.2689238

```
## Agriculture:factor(CatholicBin)1 0.08913512 0.17610660 0.5061430
##                                     Pr(>|t|)
## (Intercept)                      1.919379e-16
## Agriculture                      3.361364e-01
## factor(CatholicBin)1             7.892745e-01
## Agriculture:factor(CatholicBin)1 6.153416e-01
```

---

## Fitted lines



## Just to show you it can be done

```
summary(lm(Fertility ~ Agriculture + Agriculture : factor(CatholicBin), data = swiss))$coef
```

```
##                                     Estimate Std. Error   t value
## (Intercept)                      62.63037278  4.22989475  14.8066031
## Agriculture                      0.08539357  0.08945287   0.9546209
## Agriculture:factor(CatholicBin)1  0.13339603  0.06198753   2.1519817
##                                     Pr(>|t|)
## (Intercept)                      1.056741e-18
## Agriculture                      3.449849e-01
## Agriculture:factor(CatholicBin)1  3.692561e-02
```