



# Multivariable regression

## Regression

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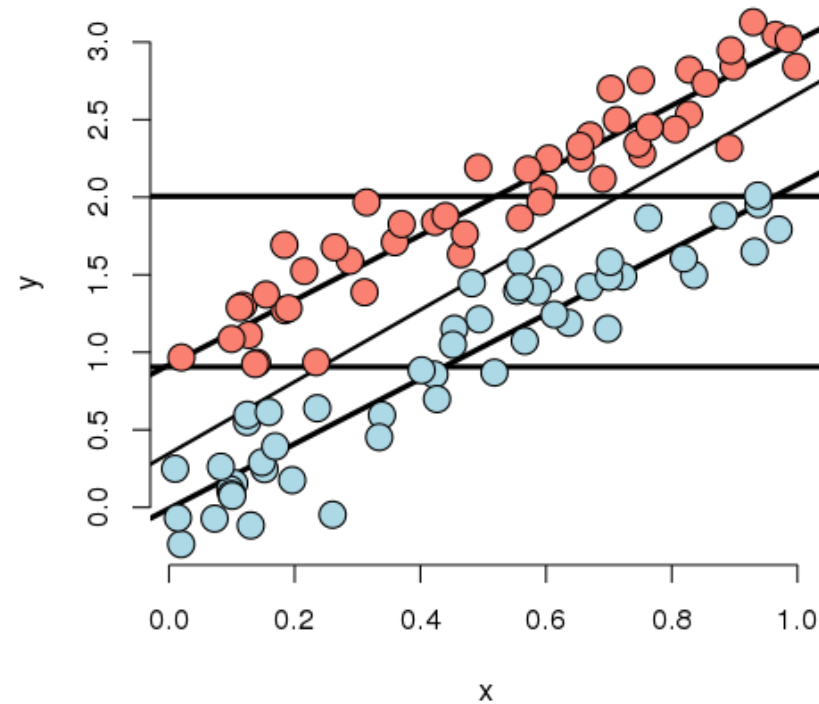
# Consider the following simulated data

Code for the first plot, rest omitted (See the git repo for the rest of the code.)

```
t = [0, 0, 0, ...(n/2 times), 1, 1, 1, ... (n/2 times)] <- t for Treatment

n <- 100; t <- rep(c(0, 1), c(n/2, n/2)); x <- c(runif(n/2), runif(n/2));
beta0 <- 0; beta1 <- 2; tau <- 1; sigma <- .2
y <- beta0 + x * beta1 + t * tau + rnorm(n, sd = sigma)
plot(x, y, type = "n", frame = FALSE)
abline(lm(y ~ x), lwd = 2)
abline(h = mean(y[1 : (n/2)]), lwd = 3)      mean of treatment = 0
abline(h = mean(y[(n/2 + 1) : n]), lwd = 3) mean of treatment = 1
fit <- lm(y ~ x + t)
abline(coef(fit)[1], coef(fit)[2], lwd = 3)
abline(coef(fit)[1] + coef(fit)[3], coef(fit)[2], lwd = 3)
points(x[1 : (n/2)], y[1 : (n/2)], pch = 21, col = "black", bg = "lightblue", cex = 2)
points(x[(n/2 + 1) : n], y[(n/2 + 1) : n], pch = 21, col = "black", bg = "salmon", cex = 2)
```

# Simulation 1



der Unterschied zwischen  $t=1$  und  $t=0$  ist ungefähr gleich, egal ob man  $x$  berücksichtigt oder nicht.

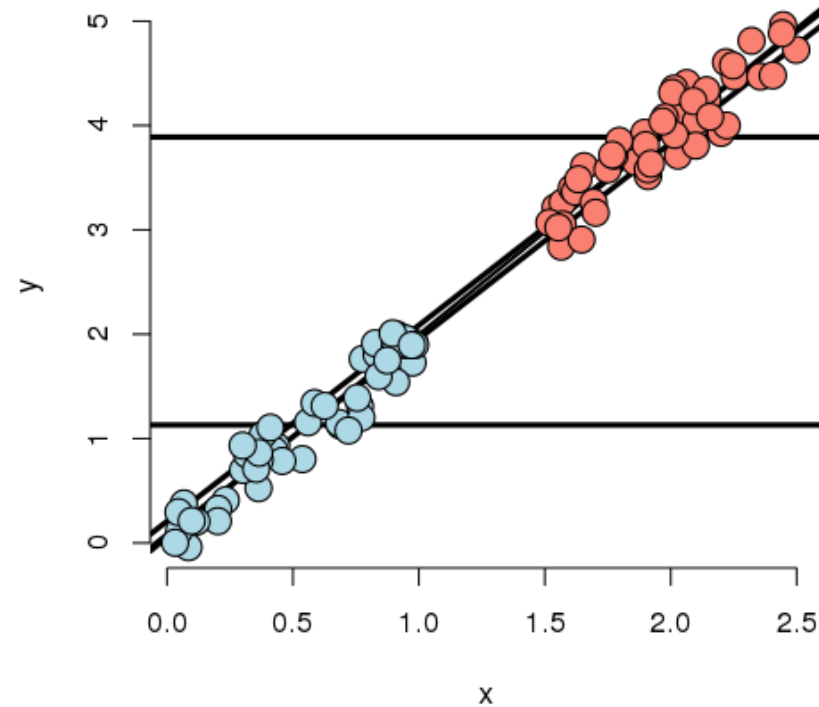
vgl Abstand dieser beiden mean-Linien und obiger Abstand der beiden Regressionslinien.

# Discussion

## Some things to note in this simulation

- The X variable is unrelated to group status dh. unabhaengig von X kommen etwa gleich viele t=0 und t=1 -Punkte vor (?)
- The X variable is related to Y, but the intercept depends on group status.
- The group variable is related to Y. t=0 (blau) hat niedrigeres Y als t=1 (rot)
  - The relationship between group status and Y is constant depending on X.
  - The relationship between group and Y disregarding X is about the same as holding X constant  
dh. der Abstand zwischen den Mean-Linien (die also den Einfluss von X nicht beruecksichtigen ist immer etwa gleich wie jener zwischen den beiden Regressionslinien (die also den Einfluss von X beruecksichtigen)

# Simulation 2



Unterschied zw mean  $t=0$  und  
mean  $t=1$ : massive

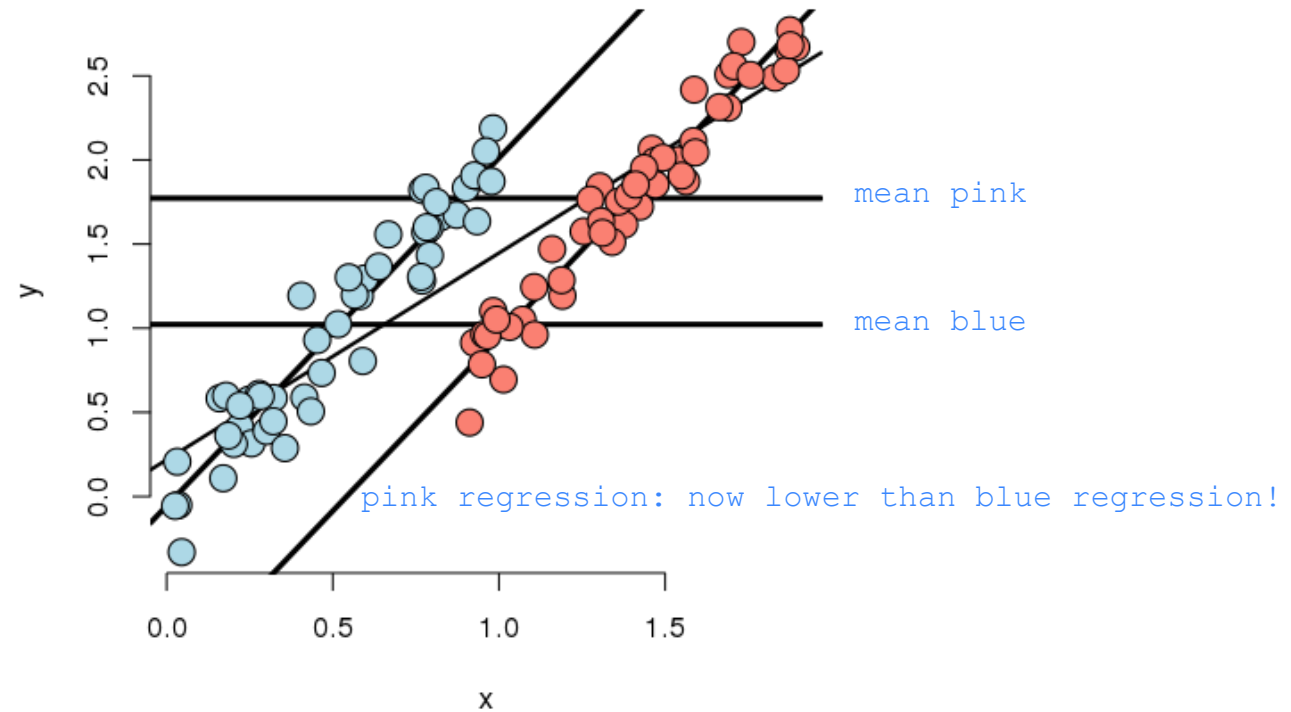
Aber wenn man den Einfluss von  
 $x$  beruecksichtigt, verschwindet  
er (Intercept und Slope  
fast gleich).

# Discussion

## Some things to note in this simulation

- The X variable is highly related to group status *If I told you X, you'd know the group status (1 or 0)*
  - The X variable is related to Y, the intercept doesn't depend on the group variable.
    - The X variable remains related to Y holding group status constant
  - The group variable is marginally related to Y disregarding X.
  - The model would estimate no adjusted effect due to group.
    - There isn't any data to inform the relationship between group and Y.
    - This conclusion is entirely based on the model.
- Allerdings haben wir fuer die rosa Gruppe keine Daten nahe beim Intercept, es haengt also voellig vom Modell ab.*
- So the group means are very different – if we ignore X!*
- The blue group seems to be linearly related to Y if you only look at it. Same for the pink group.*
- 'adjusted' means considering X. Unadjusted (eg. only the group means): there is a huge effect.*

# Simulation 3



so: treatment effect reverses itself when you consider ("adjust for") x!

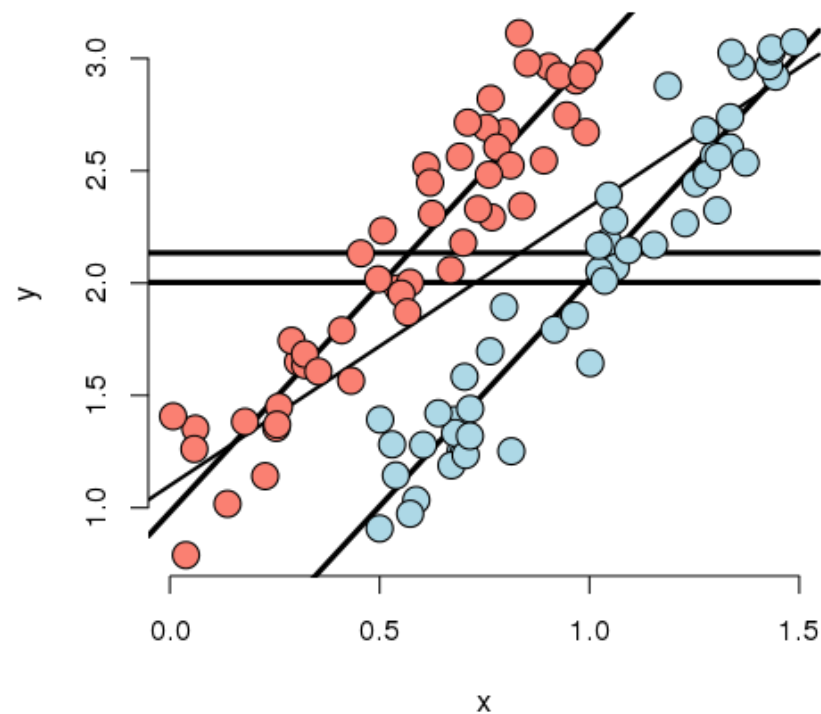
# Discussion

Some things to note in this simulation

- Marginal association has red group higher than blue.
- Adjusted relationship has blue group higher than red.
- Group status related to X.
- There is some direct evidence for comparing red and blue holding X fixed.



# Simulation 4



hardly any difference between treatments when we don't adjust for x.

If we do: a clear difference.

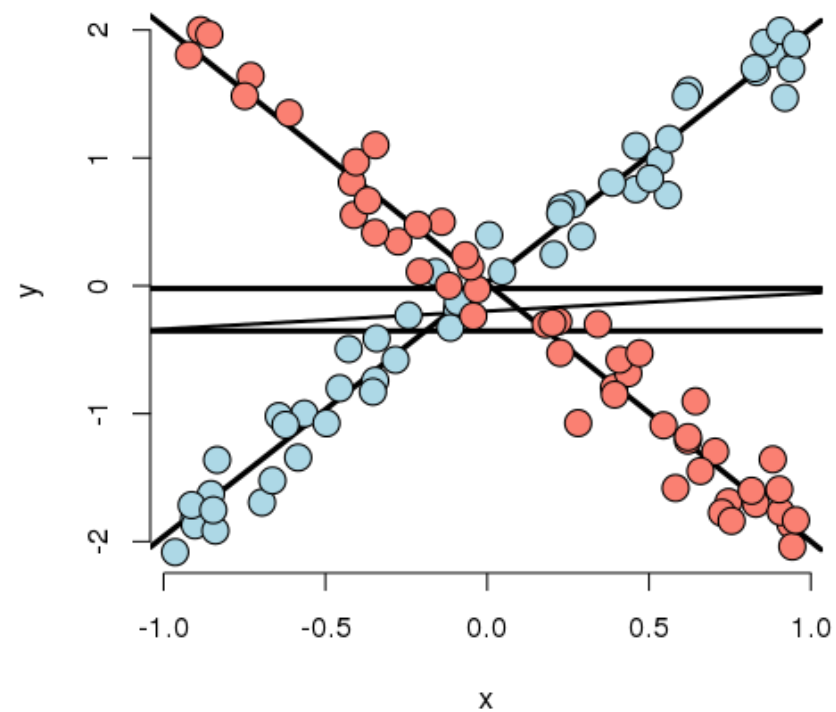
# Discussion

Some things to note in this simulation

- No marginal association between group status and Y.
- Strong adjusted relationship.
- Group status not related to X.
- There is lots of direct evidence for comparing red and blue holding X fixed.

# Simulation 5

An Interaction:



Interaction

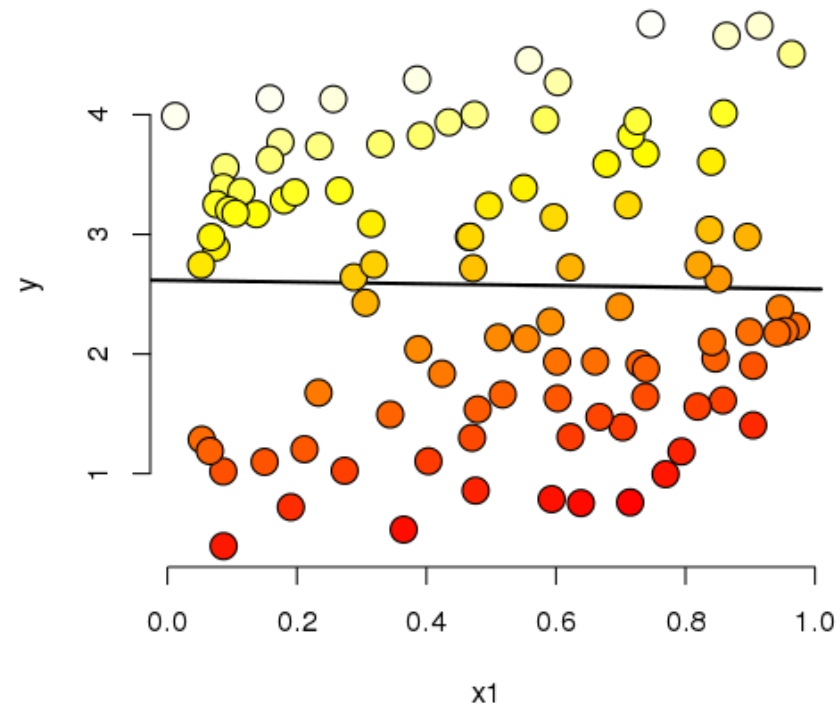
no treatment effect

# Discussion

Some things to note from this simulation

- There is no such thing as a group effect here.
  - The impact of group reverses itself depending on X.
  - Both intercept and slope depends on group.
- Group status and X unrelated.
  - There's lots of information about group effects holding X fixed.

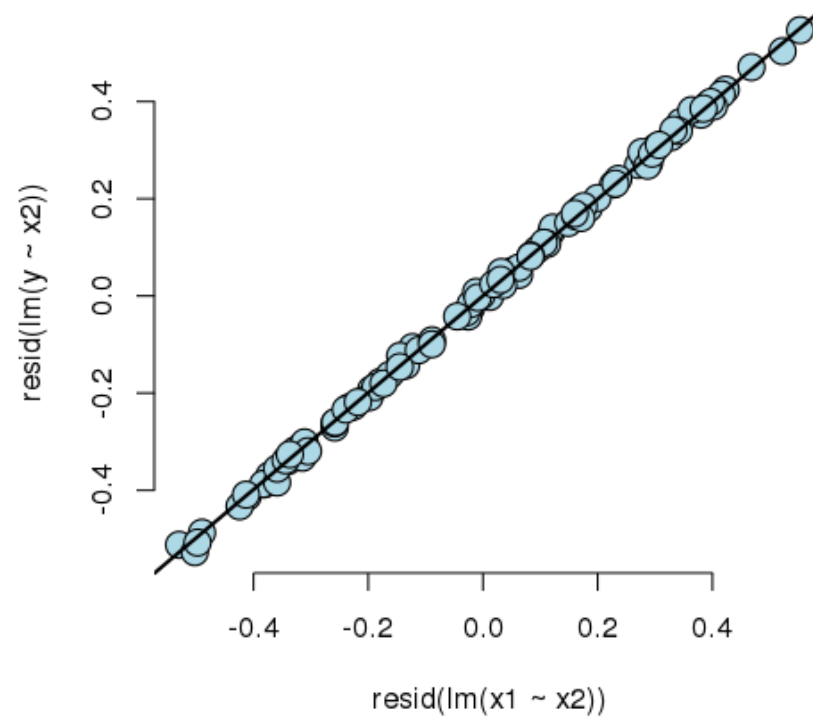
## Simulation 6



Do this to investigate the bivariate relationship

```
library(rgl)  
plot3d(x1, x2, y)
```

## Residual relationship



# Discussion

Some things to note from this simulation

- X1 unrelated to X2
- X2 strongly related to Y
- Adjusted relationship between X1 and Y largely unchanged by considering X2.
  - Almost no residual variability after accounting for X2.



# Some final thoughts

- Modeling multivariate relationships is difficult. `if you want to interpret them!`  
`Prediction alone is easier.`
- Play around with simulations to see how the inclusion or exclusion of another variable can change analyses.
- The results of these analyses deal with the impact of variables on associations.
  - Ascertaining mechanisms or `cause` are difficult subjects to be added on top of difficulty in understanding multivariate associations.

`causal interference is of course 'difficult'`