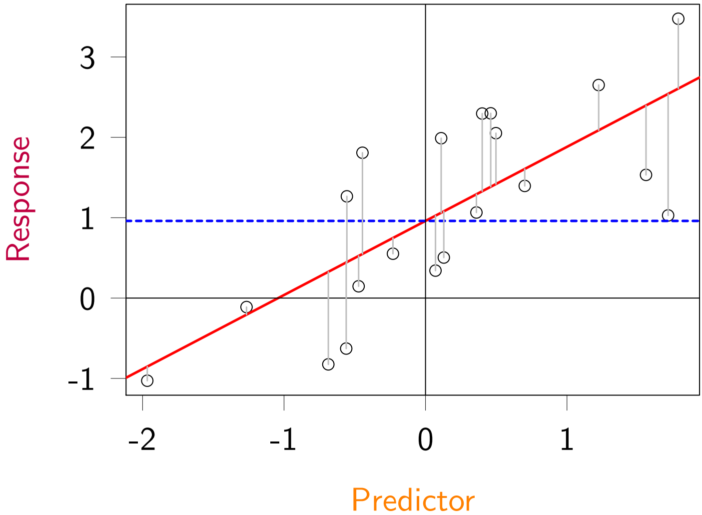
What on earth is going on with my linear models??!

March 8, 2018

A simple linear model

Response = **Intercept** + **Slope** $\times$ **Predictor** + **Error**



A simple linear model

Response = **Intercept** + **Slope** $\times$ **Predictor** + **Error**

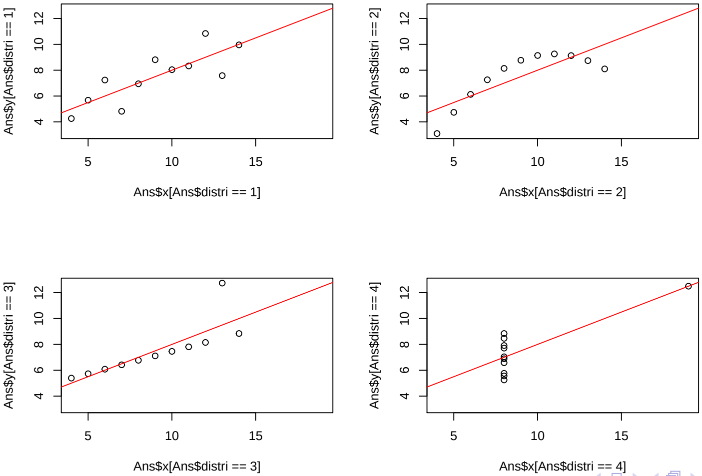
In R:

```
lm(response ~ 1 + predictor1 + predictor2, data=data)
  # equivalent to
lm(response ~ predictor1 + predictor2, data=data)
```

- Intercept can be explicit or implicit
- Can remove intercept with `...~ 0 + ...`
- Error is implicit
- Feed the option `data=` to keep code short, reliable and flexible
- Order of predictors do not matter

Why we need checks: summary(lm) isn't enough

```r
Ans <- read.csv(file = "Anscombe.csv")
```



General approach

1. Scientific question

2. Model and Statistical question ⟷ 3. Data collection

4. Estimation

4.b Uncertainty and statistical significance

5. Diagnostic, check assumptions, prediction

6. Interpret and think about the biology

Why we need checks: missing a relationship

```
forprediction <- read.csv(file = "forprediction.csv")
```

Does "predictor" predict "obs"?

Why we need checks: missing a relationship

```
forprediction <- read.csv(file = "forprediction.csv")
```

Does "predictor" predict "obs"?

```
summary(lm(obs ~ 1 + predictor, data=forprediction) )
```

Why we need checks: missing a relationship

Does "predictor" predict "obs"? Apparently not:

```
summary(lm(obs ~ 1 + predictor, data=forprediction) )

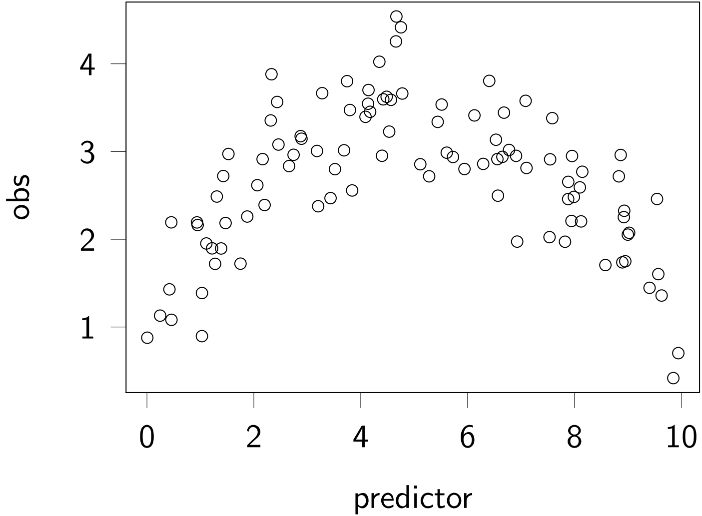

Call:
lm(formula = obs ~ 1 + predictor, data = forprediction)

Residuals:
    Min      1Q  Median      3Q     Max
-2.1962 -0.5326  0.1378  0.5785  1.8664

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.72530    0.16953  16.076   <2e-16 ***
predictor   -0.01129    0.02956  -0.382    0.703
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8382 on 98 degrees of freedom
```

Why we need checks: missing a relationship



How to check?

```
m0 <- lm(obs ~ 1 + predictor, data=forprediction)
summary(m0)


Call:
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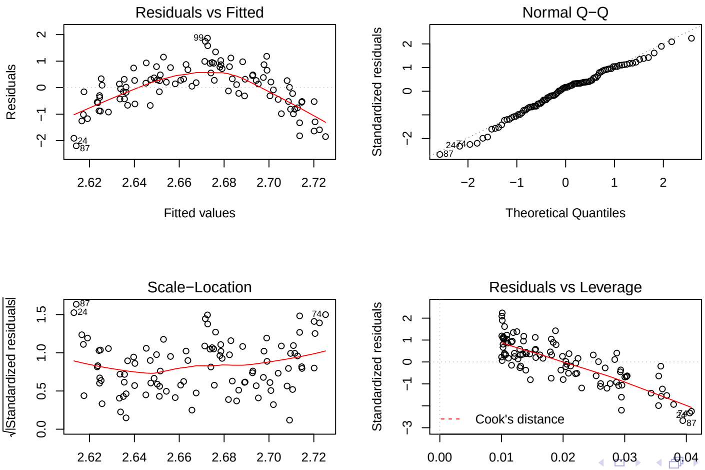
How to check?

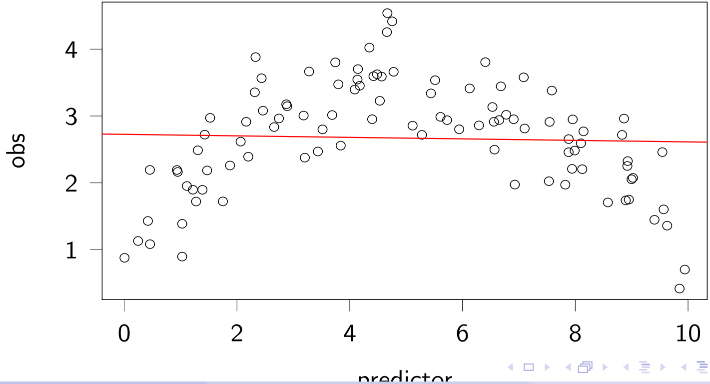
```
par(mfrow=c(2,2))
  plot(m0)
```



How to check?

```
m0 <- lm(obs ~ 1 + predictor, data=forprediction)
```

```
    setPar()
plot(x=forprediction$predictor, y=forprediction$obs, xlab="predicto
abline(m0, col="red", lwd=3) #simple prediction, without SE
```



Check checklist

- **Visualize your data**
- Residual in summary(): are they symmetrical?
- plot(lm):
  1. trend residual/fitted?
  2. Normal residuals?
  3. trend in residual variance?
  4. outliers?
- Predictions: range and biological meaning

Practice lm() with parasites

What explains variation in parasitic load?

You collected ecto-parasites on some furry large mammals at three locations. Parasites break easily when we collect them and are impossible to count, so we decide to measure parasitic load as their mass. **Why do some mammals have larger parasitic load?**

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- Load the `Para.csv` data (don't forget: str(), summary(), plot()...)
- Model `Parasite_Mass` using `lm()`
- Find what variables predict `Parasite_Mass`
- How good are your models? Assumptions? Prediction?
- What biological interpretation can you imagine?

Multiple regression

Transformations

Linear model basic assumptions

Not necessarily wrong, but typical interpretation assumes:

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  Risk: Over-optimistic uncertainty, unreliable predictions
- Independence of error
  Risk: Bias and over-optimistic uncertainty

Extra exercises

General R coding

1. What is the fastest way to get row averages in a data-frame?
2. Create a function called colVars, like colMeans but for variance
3. Create nice plots to visualize iris data (ideally journal-quality)

Linear models

1. Load Cdata.csv, fit models of y predited by x1 and x2, or x2 and x3. Something is weird, what is going on? What to do?
2. For model that can be fitted with t.test, aov, and lm, is one of the function faster?
3. Write your own code to obtain a prediction from a lm (that is, a simpler version of the predict function), with confidence interval. (extra toughness: do it using the matrix formulation of the analytical solution to a linear model)

What do you want to learn about?

Topics

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