# Linear models

### Example dataset: forest trees

Go to https://tinyurl.com/treesdata

```
trees <- read.csv("data-raw/trees.csv")
head(trees)</pre>
```

```
plot dbh height sex dead
1 4 29.68 36.1 male 0
2 5 33.29 42.3 male 0
3 2 28.03 41.9 female 0
4 5 39.86 46.5 female 0
5 1 47.94 43.9 female 0
6 1 10.82 26.2 male 0
```

### Example dataset: forest trees

- Go to https://tinyurl.com/treesdata
- Download zip file and uncompress (within your project folder!)

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## Questions

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- ▶ Do taller trees have bigger trunks?

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- ▶ Do taller trees have bigger trunks?
- ► Can we predict height from DBH? How well?

# Always plot your data first!

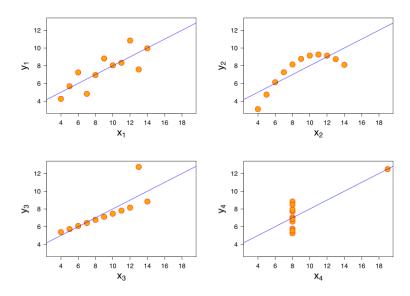
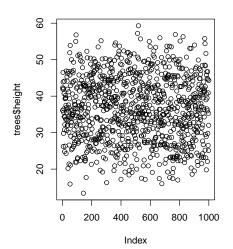


Figure 1:

# Exploratory Data Analysis (EDA)

Outliers

```
plot(trees$height)
```



# Outliers impact on regression

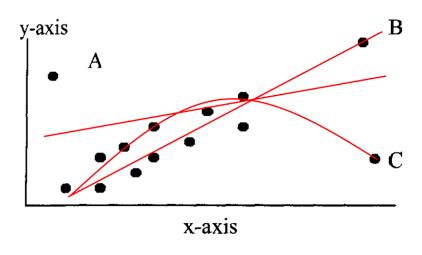
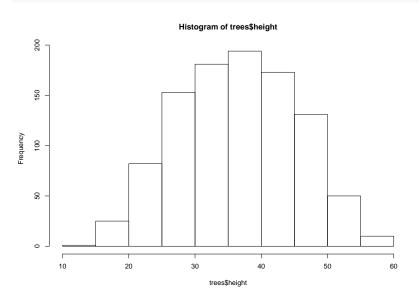


Figure 2:

See http://rpsychologist.com/d3/correlation/

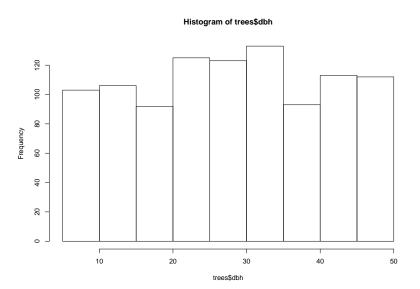
# Histogram of response variable

hist(trees\$height)



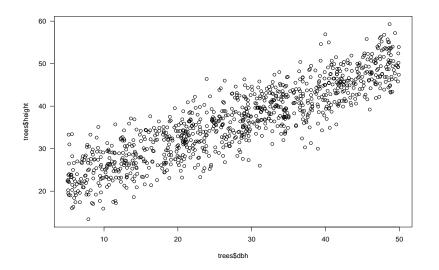
# Histogram of predictor variable

hist(trees\$dbh)



# Scatterplot

```
plot(trees$dbh, trees$height, las = 1)
```



## Now fit model

Hint: 1m

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```
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```

```
m1 <- lm(height ~ dbh, data = trees)</pre>
```

### What does this mean?

```
Call:
lm(formula = height ~ dbh, data = trees)
Residuals:
   Min 1Q Median
                          30
                                Max
-13.3270 -2.8978 0.1057 2.7924 12.9511
Coefficients:
         Estimate Std. Error t value Pr(>|t|)
dbh 0.61570 0.01013 60.79 <2e-16 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 4.093 on 998 degrees of freedom
```

Multiple R-squared: 0.7874, Adjusted R-squared: 0.7871 F-statistic: 3695 on 1 and 998 DF, p-value: < 2.2e-16

# Retrieving model coefficients

#### coef(m1)

```
(Intercept) dbh
19.3391968 0.6157036
```

### Confidence intervals

#### confint(m1)

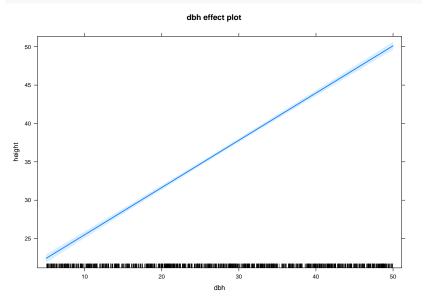
```
2.5 % 97.5 % (Intercept) 18.7296053 19.948788 dbh 0.5958282 0.635579
```

# Using effects package

```
library(effects)
summary(allEffects(m1))
model: height ~ dbh
dbh effect
dbh
      5
              20 30
                             40
                                        50
22.41771 31.65327 37.81030 43.96734 50.12438
Lower 95 Percent Confidence Limits
dbh
              20 30
                             40
                                        50
21,89682, 31,35487, 37,55287, 43,61733, 49,61669
Upper 95 Percent Confidence Limits
dbh
              20 30
      5
                             40
                                        50
22 93861 31 95167 38 06774 44 31735 50 63207
```

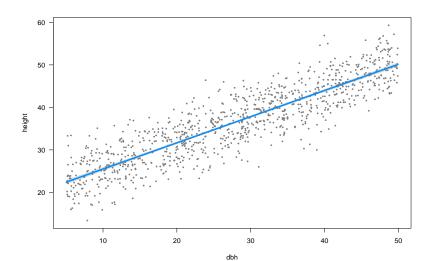
### Plot effects





# Plot model (visreg)

```
library(visreg)
visreg(m1)
```



► Linearity (transformations, GAM...)

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- ► Residuals:

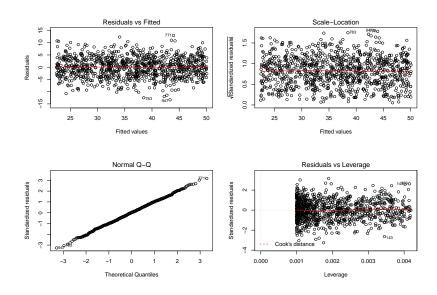
- ► Linearity (transformations, GAM...)
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  - Independent

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  - Equal variance
  - Normal

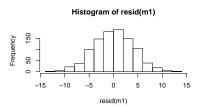
- ► Linearity (transformations, GAM...)
- ► Residuals:
  - Independent
  - Equal variance
  - Normal
- ▶ No measurement error in predictors

# Model checking: residuals



### Are residuals normal?

#### hist(resid(m1))



SD of residuals = 4.09 coincides with estimate of sigma.

# How good is the model in predicting tree height?

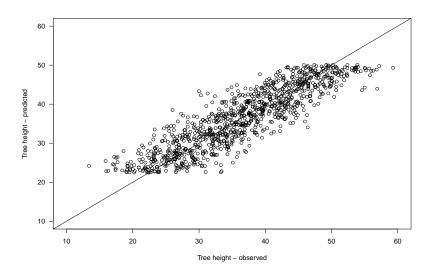
fitted gives predictions for each observation

```
trees$height.pred <- fitted(m1)
head(trees)</pre>
```

```
plot dbh height sex dead height.pred
    4 29.68 36.1 male
                            37.61328
   5 33.29 42.3 male 0
                            39.83597
3
   2 28.03 41.9 female 0
                            36.59737
4
 5 39.86 46.5 female
                            43.88114
5
 1 47.94 43.9 female 0
                            48.85603
6
    1 10.82 26.2 male
                        0
                            26.00111
```

# Calibration plot: Observed vs Predicted values

```
plot(trees$height, trees$height.pred, xlab = "Tree height - obse
```



# Using fitted model for prediction

Q: Expected tree height if DBH = 39 cm?

```
new.dbh <- data.frame(dbh = c(39))
predict(m1, new.dbh, se.fit = TRUE)
$fit
43.35164
$se.fit
[1] 0.1715514
$df
[1] 998
$residual.scale
[1] 4.092629
```

▶ plot

- ▶ plot
- summary

- ▶ plot
- ▶ summary
- ▶ coef

- ▶ plot
- ▶ summary
- ▶ coef
- ▶ confint

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# Important functions

- ▶ plot
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- ▶ plot
- summary
- ▶ coef
- ▶ confint
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- ▶ resid
- ▶ allEffects

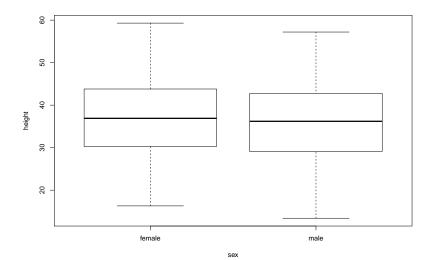
# Important functions

- ▶ plot
- ▶ summary
- ▶ coef
- ► confint
- ▶ fitted
- ▶ resid
- ▶ allEffects
- ▶ predict

# Categorical predictors (factors)

## Q: Does tree height vary with sex?

```
plot(height ~ sex, data = trees)
```



## Model height ∼ sex

```
m2 <- lm(height ~ sex, data = trees)
Call:
lm(formula = height ~ sex, data = trees)
Residuals:
    Min 10 Median 30 Max
-22.6881 -6.7881 -0.0097 6.7261 22.3687
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 36.9312 0.3981 92.778 <2e-16 ***
sexmale -0.8432 0.5607 -1.504 0.133
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 8.865 on 998 degrees of freedom
```

Multiple R-squared: 0.002261, Adjusted R-squared: 0.001261 F-statistic: 2.261 on 1 and 998 DF, p-value: 0.133

## Linear model with categorical predictors

$$y_i = a + bx_i + \varepsilon_i$$
$$y_i = a + b_{male} + \varepsilon_i$$

## Model height ∼ sex

```
m2 <- lm(height ~ sex, data = trees)
Call:
lm(formula = height ~ sex, data = trees)
Residuals:
    Min 10 Median 30 Max
-22.6881 -6.7881 -0.0097 6.7261 22.3687
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 36.9312 0.3981 92.778 <2e-16 ***
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# Effects: Height $\sim$ sex

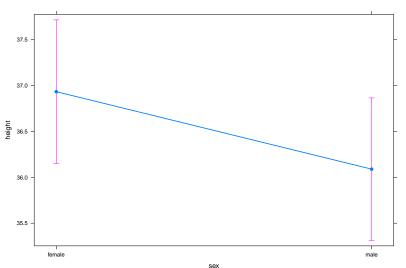
Compare Cls

```
summary(allEffects(m2))
 model: height ~ sex
 sex effect
sex
  female male
36.93125 36.08810
Lower 95 Percent Confidence Limits
sex
  female male
36, 15012, 35, 31319
Upper 95 Percent Confidence Limits
sex
  female male
37.71238 36.86300
```

#### Plot

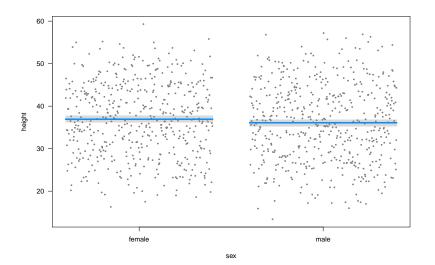
#### plot(allEffects(m2))



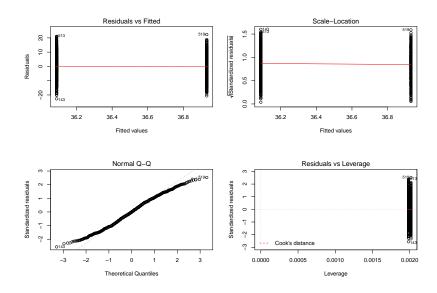


# Plot (visreg)

#### visreg(m2)

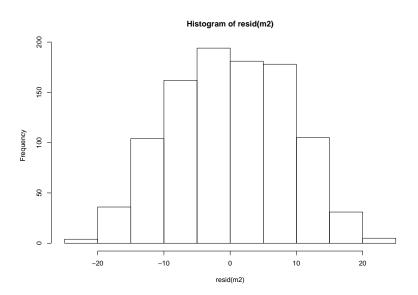


# Model checking: residuals



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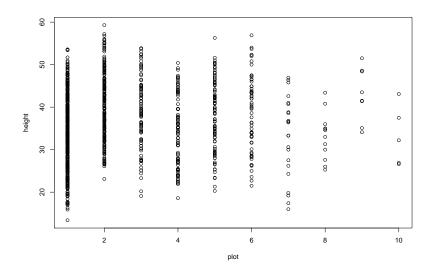
hist(resid(m2))



Q: Does height differ among field plots?

#### Plot data first

```
plot(height ~ plot, data = trees)
```



## Linear model with categorical predictors

$$y_i = a + bx_i + \varepsilon_i$$
 
$$y_i = a + b_{plot2} + c_{plot3} + d_{plot4} + e_{plot5} + \dots + \varepsilon_i$$

#### Model Height ~ Plot

All right here?

```
m3 <- lm(height ~ plot, data = trees)
```

```
Call:
```

```
lm(formula = height ~ plot, data = trees)
```

#### Residuals:

Min	1Q	Median	3Q	Max
-22.4498	-6.7049	0.0709	6.7537	23.0640

#### Coefficients:

plot 0.3862 0.1413 2.733 0.00639 \*\*
--Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8.842 on 998 degrees of freedom Multiple R-squared: 0.007429, Adjusted R-squared: 0.006435

#### Plot is a factor!

```
trees$plot <- as.factor(trees$plot)</pre>
```

#### Model Height ∼ Plot

```
Call:
lm(formula = height ~ plot, data = trees)
Residuals:
    Min
             10 Median
                            30
                                   Max
-20.4416 -6.9004 0.0379 6.3051
                               19.7584
Coefficients:
          Estimate Std. Error t value Pr(>|t|)
(Intercept) 33.8416
                     0.4266 79.329 < 2e-16 ***
plot2
           6.3411 0.7126 8.899 < 2e-16 ***
plot3
           4.9991 0.9828 5.086 4.36e-07 ***
plot4
           0.5329 0.9872 0.540 0.58949
        4.3723 0.9425 4.639 3.97e-06 ***
plot5
plot6
        4.7601 1.1709 4.065 5.18e-05 ***
plot7 -0.7416 1.8506 -0.401 0.68871
         -0.6832 2.4753 -0.276 0.78258
plot8
           9.1709 3.0165 3.040 0.00243 **
plot9
plot10
         -0.5816
                     3.8013 -0.153 0.87843
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
Residual standard error: 8.446 on 990 degrees of freedom
Multiple R-squared: 0.1016, Adjusted R-squared: 0.09344
```

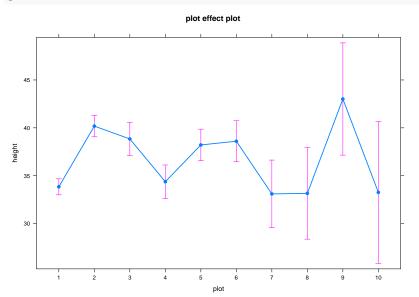
F-statistic: 12.44 on 9 and 990 DF. p-value: < 2.2e-16

#### Estimated tree heights for each site

```
summary(allEffects(m3))
 model: height ~ plot
 plot effect
plot
33.84158 40.18265 38.84066 34.37444 38.21386 38.60167 33.10000 33.15833
               10
43.01250 33.26000
Lower 95 Percent Confidence Limits
plot
33.00444 39.06264 37.10317 32.62733 36.56463 36.46190 29.56629 28.37367
               10
37.15251 25.84764
Upper 95 Percent Confidence Limits
plot
34.67872 41.30265 40.57814 36.12156 39.86309 40.74143 36.63371 37.94299
               10
48.87249 40.67236
```

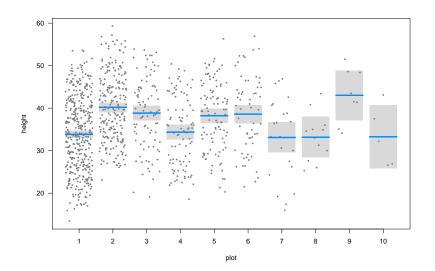
## Plot

#### plot(allEffects(m3))

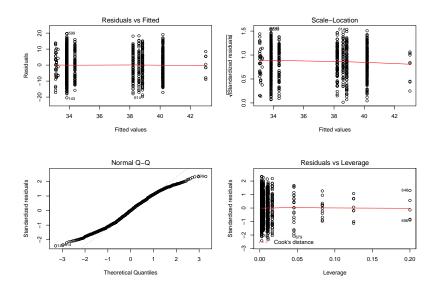


# Plot (visreg)

#### visreg(m3)



# Model checking: residuals





# Predicting tree height based on dbh and site

$$y_i = a + bx_i + \varepsilon_i$$
  
$$y_i = a + b_{plot2} + c_{plot3} + d_{plot4} + e_{plot5} + \dots + k \cdot DBH_i + \varepsilon_i$$

#### Predicting tree height based on dbh and site

```
Call:
lm(formula = height ~ plot + dbh, data = trees)
Residuals:
    Min
                 Median
             10
                              30
                                     Max
-10.1130 -1.9885 0.0582 2.0314 11.3320
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 16.699037
                     0.260565
                              64.088 < 2e-16 ***
plot2
          6.504303  0.256730  25.335  < 2e-16 ***
          4.357457 0.354181 12.303 < 2e-16 ***
plot3
plot4
         1.934650 0.356102 5.433 6.98e-08 ***
plot5
        3.637432
                     0.339688 10.708 < 2e-16 ***
plot6 4.204511
                     0.421906 9.966 < 2e-16 ***
plot7
       -0.176193
                     0.666772 -0.264 0.7916
                     0.893603 -5.945 3.82e-09 ***
plot8
         -5.312648
plot9
         5.437049
                     1.087766 4.998 6.84e-07 ***
plot10
        2.263338 1.369986 1.652 0.0988 .
dbh
           0.617075
                     0.007574 81.473 < 2e-16 ***
---
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
Residual standard error: 3.043 on 989 degrees of freedom
Multiple R-squared: 0.8835, Adjusted R-squared: 0.8823
F-statistic: 750 on 10 and 989 DF, p-value: < 2.2e-16
```

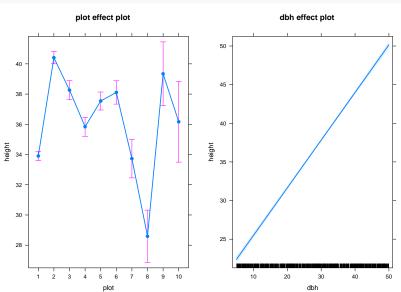
#### Estimated tree heights for each site

22.38634 31.64246 37.81321 43.98396 50.15471

summary(allEffects(multreg)) model: height ~ plot + dbh plot effect plot 33.90437 40.40868 38.26183 35.83902 37.54181 38.10889 33.72818 28.59173 10 39.34142 36.16771 Lower 95 Percent Confidence Limits plot 33.60276 40.00512 37.63569 35.20858 36.94739 37.33787 32.45495 26.86438 10 37.22831 33.49623 Upper 95 Percent Confidence Limits plot 34.20599 40.81223 38.88798 36.46947 38.13622 38.87990 35.00141 30.31907 10 41.45454 38.83919 dbh effect dbh 20 30

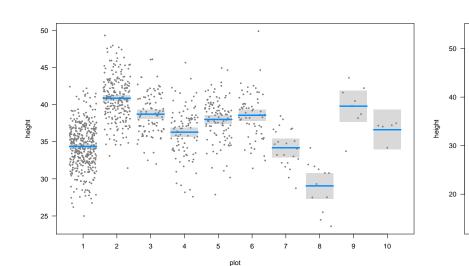
#### Plot

#### plot(allEffects(multreg))

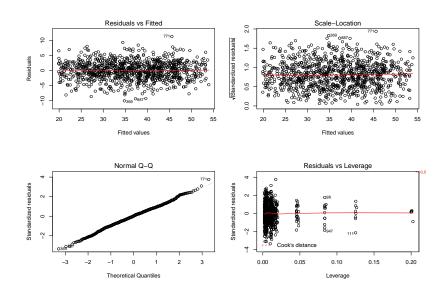


# Plot (visreg)

#### visreg(multreg)



# Model checking: residuals



#### Extra exercises

paperplanes: How does flight distance differ with age, gender or paper type?

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- mammal sleep: Are sleep patterns related to diet?

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- paperplanes: How does flight distance differ with age, gender or paper type?
- mammal sleep: Are sleep patterns related to diet?
- ▶ iris: Predict petal length ~ petal width and species