

# Introduction to Statistical Modeling

Predictivity and variability

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# Prediction

## Example

Use model to predict length of larch based on mineral composition of needles.

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	160.66283	175.61424	0.9148622	0.370649894
nitrogen	-76.49677	92.34000	-0.8284250	0.416746264
phosphor	-1120.70470	711.42841	-1.5752881	0.130135986
potassium	138.06170	41.29966	3.3429260	0.003084272
nitrogen:phosphor	724.38231	353.05353	2.0517634	0.052870451

- Percentages: nitrogen = 1.9, phosphorus = 0.2, potassium = 0.7.
- Predicted **average** length:

$$160.66 - 76.5 \times 1.9 - 1120.7 \times 0.2 + 138.06 \times 0.7 + \\ 724.38 \times 1.9 \times 0.2 = 163.1.$$

# Accuracy of prediction

To determine the accuracy of a prediction, we need to take into account the

- **variability** of the observations around the regression line
- **precision** of the estimated regression line.

## Estimating variability via the residual standard error

Residual standard error (RSE):

- CWD basal area: 1.01 on 13 degrees of freedom
- Larches: 35.55 on 21 degrees of freedom.

Residual standard deviation tells that 95% of lengths, given nitrogen, phosphorus and potassium percentages of 1.9, 0.2 and 0.7, are expected to lie within a distance

$$2 \times 35.55 = 71.1$$

of the mean.

# Residual standard error in R

Call:

```
lm(formula = length ~ nitrogen * phosphor + potassium)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-54.051	-24.544	5.934	21.866	69.243

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	160.66	175.61	0.915	0.37065
nitrogen	-76.50	92.34	-0.828	0.41675
phosphor	-1120.70	711.43	-1.575	0.13014
potassium	138.06	41.30	3.343	0.00308 **
nitrogen:phosphor	724.38	353.05	2.052	0.05287 .

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Residual standard error: 35.55 on 21 degrees of freedom

Multiple R-squared: 0.8836, Adjusted R-squared: 0.8614

F-statistic: 39.85 on 4 and 21 DF, p-value: 1.603e-09

## Residual standard error (by hand)

RSE can be calculated as

$$RSE = \sqrt{\frac{SSE}{n - p}} = \sqrt{MSE}$$

with SSE, the sum-squared of the residuals, given by

$$SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n e_i^2.$$

and  $p$  the number of parameters in the model.

For example (larches,  $p = 5$ ):

```
SSE <- sum(model_l8$residuals^2)
RSE <- sqrt(SSE/(26 - 5))
RSE
```

```
[1] 35.54858
```

# Prediction/confidence intervals

- **Prediction intervals** combine both inaccuracies
  - Variability around the regression line
  - Precision of the regression line.
- Designed to contain, with 95% confidence, a random observation (e.g. CWD basal area or tree length) for given predictor values (e.g. tree density or given proportions of nitrogen, phosphorus, and potassium)
- **Confidence intervals** incorporate only the precision of the regression line.
- Designed to contain, with 95% confidence, the **average** of random observations for given predictor values.



## Prediction intervals in R: CWD basal area

```
p <- predict(model3, newdata = data.frame(RIP.DENS=800:2200),  
            interval = "confidence")  
p[1:3,] # print first 3 predictions
```

	fit	lwr	upr
1	0.9474953	-0.1563700	2.051361
2	0.9568141	-0.1433865	2.057015
3	0.9661229	-0.1304244	2.062670

```
p <- predict(model3, newdata = data.frame(RIP.DENS=800:2200),  
            interval = "prediction")  
p[1:3,] # print first 3 predictions
```

	fit	lwr	upr
1	0.9474953	-1.497766	3.392757
2	0.9568141	-1.486795	3.400423
3	0.9661229	-1.475844	3.408090

## Prediction intervals in R: Larches

```
newdata <- data.frame(nitrogen = 1.9, phosphor = 0.2,  
                      potassium = 0.7)
```

```
newdata
```

```
   nitrogen phosphor potassium  
1      1.9      0.2      0.7
```

```
predict.lm(model_l8, newdata, interval = "confidence")
```

```
      fit      lwr      upr  
1 163.0865 140.6258 185.5472
```

```
predict.lm(model_l8, newdata, interval = "prediction")
```

```
      fit      lwr      upr  
1 163.0865  85.82246 240.3505
```

## Variability in regression models

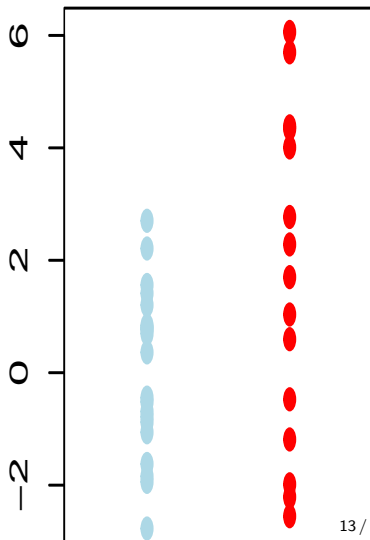
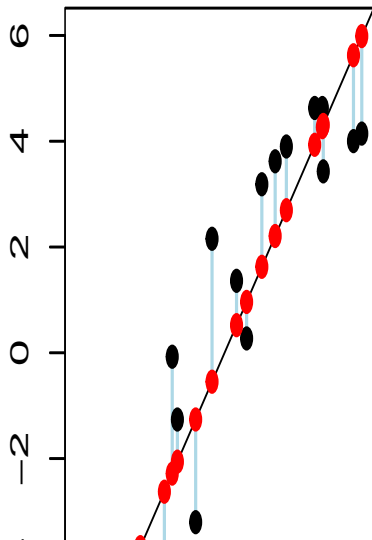
# Predictivity

Another way to gain insight in predictivity compares

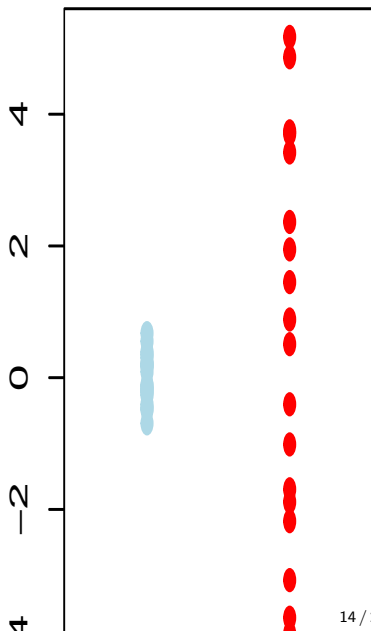
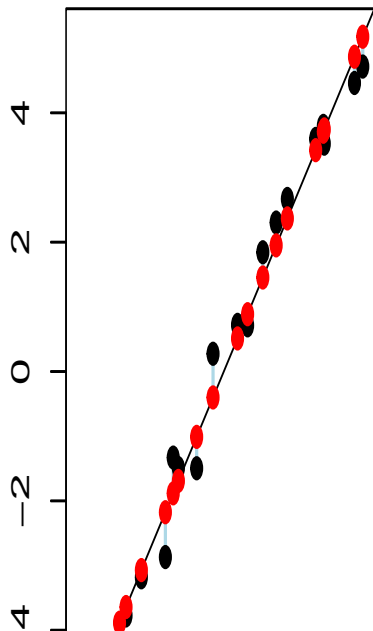
- variability **around** regression line
- with variability **on** the regression line, explained by the regression line.

## Total and residual variability

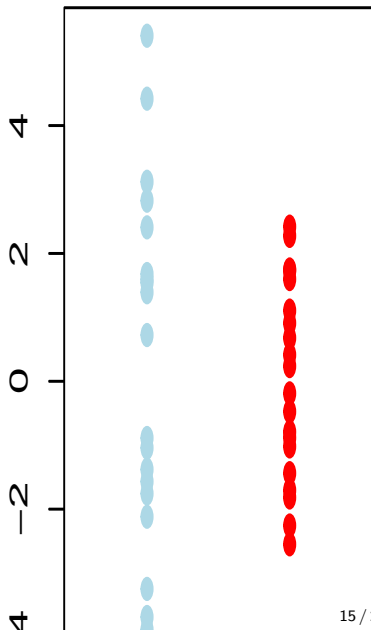
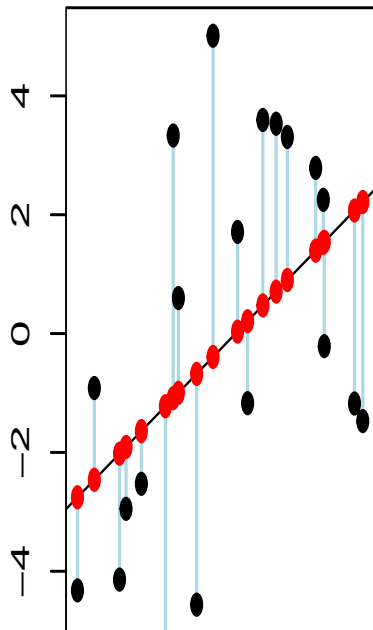
Idea: compare variability of residuals and variability of (centered) predictions.



High predictivity: low variability around line



## Low predictivity: small variability on line



# Sum of squares

- Let  $\hat{y}_i$  be the prediction for observation  $i$ , then

$$\begin{aligned} SST &= \sum_{i=1}^n (y_i - \bar{y})^2 \\ &= \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 + \sum_{i=1}^n (y_i - \hat{y}_i)^2 \\ &= \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 + \sum_{i=1}^n e_i^2 \\ &= SSR + SSE. \end{aligned}$$

- Total sum of squares (SST) = Regression sum of squares (SSR) + Residual sum of squares (SSE).
- Total variability = Variability captured by regression + Variability in residuals.



# Multiple correlation coefficient

- **Multiple correlation coefficient** or coefficient of determination:

$$R^2 = \frac{SSR}{SST}.$$

- Expresses the proportion of variability in data is captured by their association with explanatory variable.
- Measure for **predictive value** of explanatory variable.
- Always between 0 and 1.
- Simple linear regression: the square of the correlation between  $X$  and  $Y$ .

# Multiple correlation coefficient

Look at the R summary output:

- CWD basal area:

Multiple R-squared: 0.7159,      Adjusted R-squared: 0.6722

71.59% of variability on CWD basal area is explained by tree density.

- Larches:

Multiple R-squared: 0.8836,      Adjusted R-squared: 0.8614

88.36% of variability on tree length is explained by mineral composition of needles.

**Note:** High  $R^2$  only demanded for prediction, not to estimate effect of  $X$  on  $Y$

## Aside: adjusted multiple correlation coefficient

- $R^2$  always increases (gets closer to 1) when model becomes more complex
- To “punish” complexity, use adjusted  $R^2$ :

$$R_{\text{adj}}^2 = 1 - \frac{n-1}{n-p}(1 - R^2).$$

- Adjusted  $R^2$  is always lower than  $R^2$ .
- Interpretation not so straightforward, used mainly for **model comparison**.

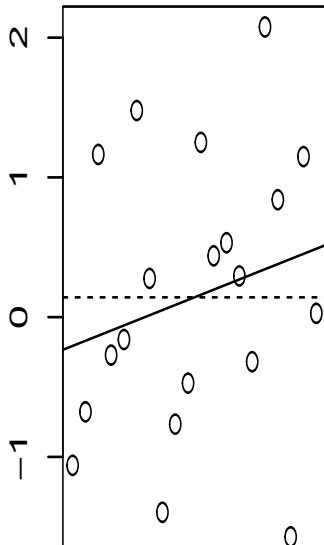
Larches:  $n = 26$ ,  $p = 5$ ,  $R^2 = 0.8836$ , so

$$R_{\text{adj}}^2 = 1 - \frac{25}{21}(1 - 0.8836) = 0.8614.$$

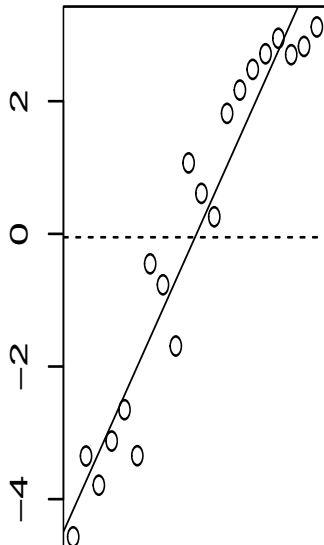
## Comparing simple vs. complex models

## Example

**Weak**



**Strong**



# Nested models

Nested models:

- Complex model: with many predictors.
- Simple model: like complex, but some predictors have been removed.

Example (larches):

- Complex:  $E(Y|X) = \alpha + \beta_N X_N + \beta_P X_P + \beta_K X_K + \beta_r X_r$
- Simple:  $E(Y|X) = \alpha + \beta_P X_P$

How do we quantify which model is better?

- Single regression: hypothesis test for  $\beta$ .
- Multiple regression: need to compare effect of **all coefficients at once**.

# Intuition: comparing variance

Idea: compare residual variability (SSE) to assess model fit.

- $SSE_{\text{complex}}$  *always* lower than  $SSE_{\text{simple}}$ .
- If it is *much* lower, decide that complex model is better.

Formalized via  $F$ -test:

- Null hypothesis: simple and complex model fit data equally well.
- Alternative hypothesis: complex model is better.
- Test statistic:

$$f = \frac{\frac{SSE_{\text{simple}} - SSE_{\text{complex}}}{p_{\text{complex}} - p_{\text{simple}}}}{\frac{SSE_{\text{complex}}}{n - p_{\text{complex}}}} \sim F_{p_{\text{complex}} - p_{\text{simple}}, n - p_{\text{complex}}}.$$

## Example: larches

Residual sum of squares:

- $SSE_{\text{simple}} = 91404.49$
- $SSE_{\text{complex}} = 30121.92$

Number of parameters:

- $p_{\text{simple}} = 2$
- $p_{\text{complex}} = 5$

Hypothesis test:

- Test statistic:  $f = 14.24139$
- $p$ -value:  $p = 0.00002744$ .

Conclusion: complex model is significantly better.



## Example in R: larches

```
model_l1 <- lm(length ~ phosphor)
model_l2 <- lm(length ~ nitrogen + phosphor + potassium + residu)
anova(model_l1, model_l2)
```

### Analysis of Variance Table

Model 1: length ~ phosphor

Model 2: length ~ nitrogen + phosphor + potassium + residu

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	24	91404				
2	21	30122	3	61283	14.241	2.744e-05 ***

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## R summary command

```
summary(model_l8)
```

(...)

Residual standard error: 35.55 on 21 degrees of freedom

Multiple R-squared: 0.8836, Adjusted R-squared: 0.8614

F-statistic: 39.85 on 4 and 21 DF, p-value: 1.603e-09

Last line:

- $F$ -statistic: compares model to model with intercept only.
- **“Is my complex model capturing something meaningful?”**