



# Statistical learning and linear regression

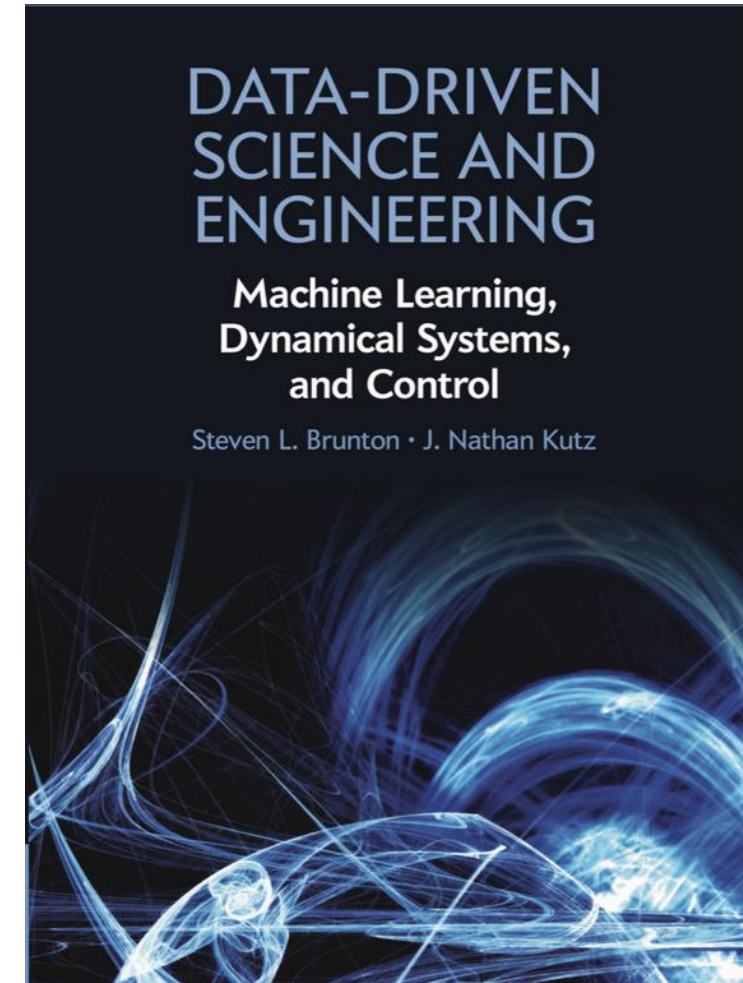
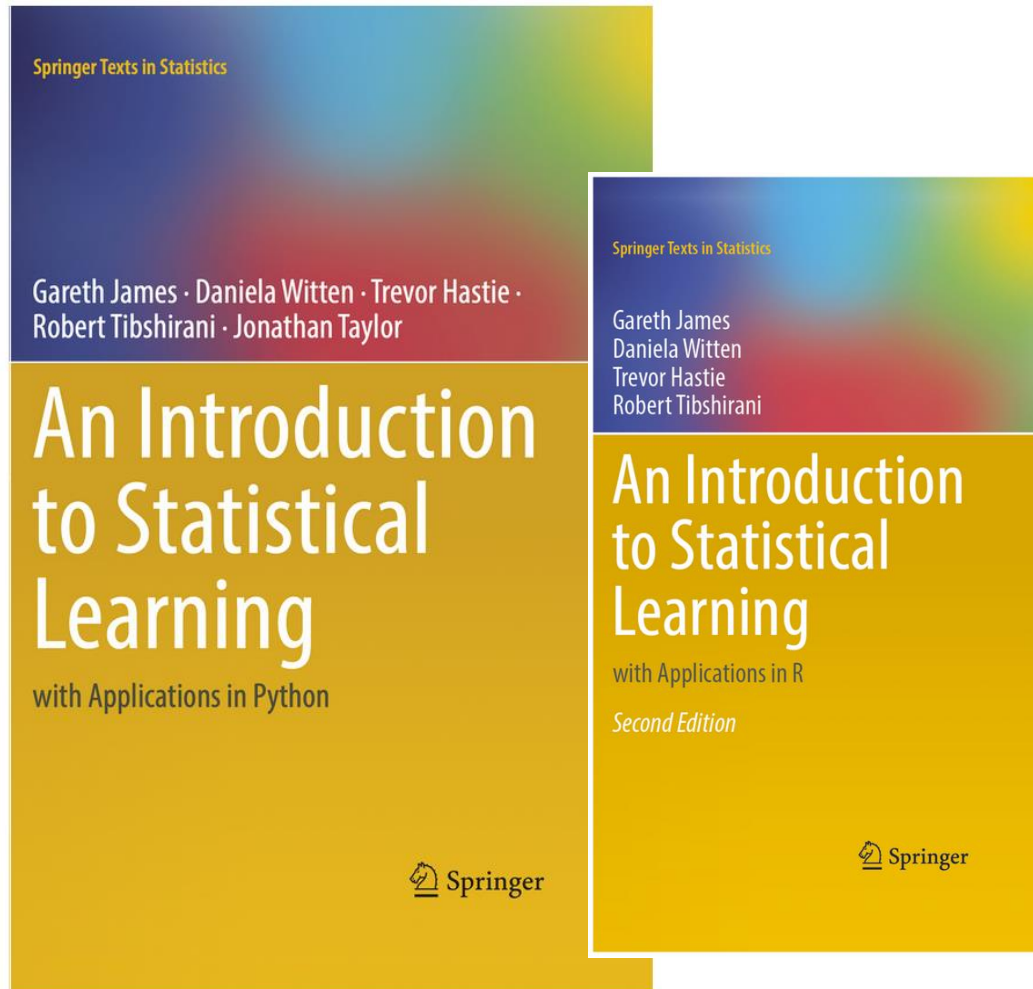
Lecture 5 of “Mathematics and AI”



# Outline

1. Supervised learning
2. Linear regression
3. Linear regression on multiple variables
4. Strengths and limitations

# Reading on statistical learning





# Supervised learning

# Supervised learning

Hello Machine ...

Let me show you some queries ...

Let me tell you the correct answers to those queries ...

Find the pattern!

Here are some queries that you haven't seen before.

Let me check how well you can answer those based on the pattern that you learned.

(What is the capitol of France?, Paris)



$(x = 0.2, y = 1.3)$

# Supervised learning

Hello Machine ...

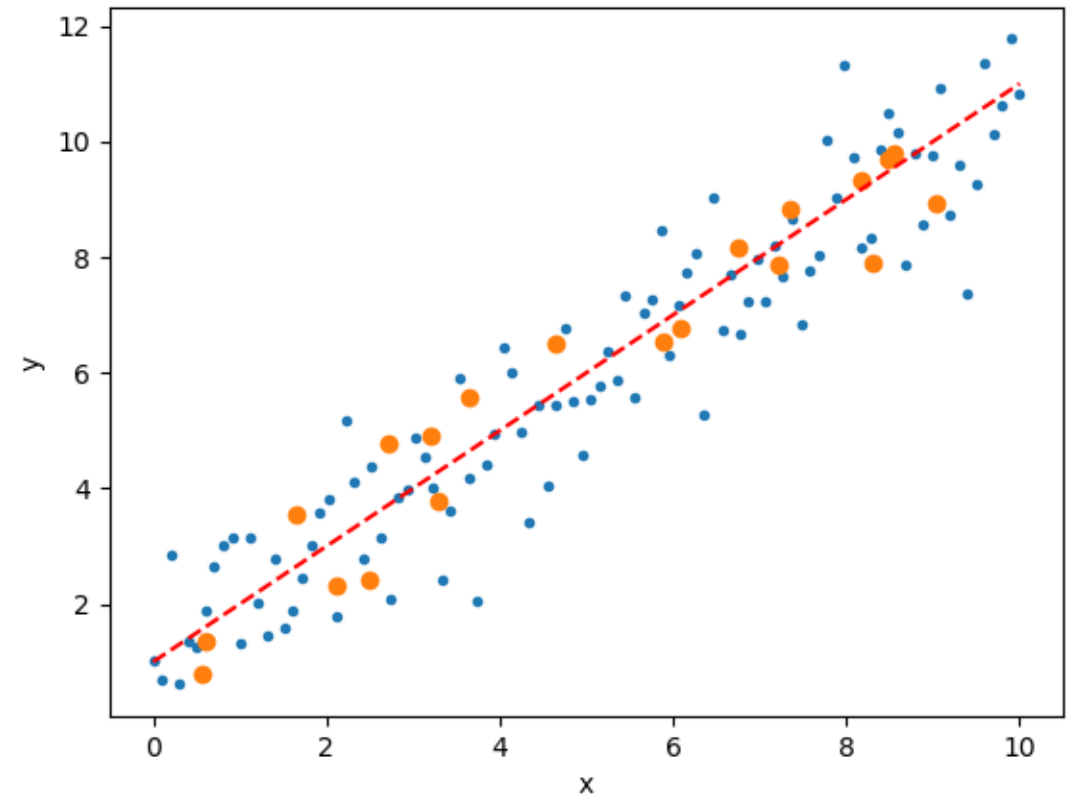
Let me show you some queries ...

Let me tell you the correct answers to those queries ...

Find the pattern!

Here are some queries that you haven't seen before.

Let me check how well you can answer those based on the pattern that you learned.

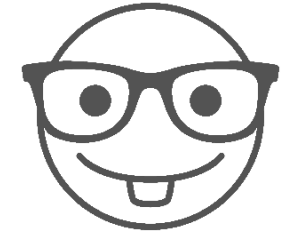


# Supervised learning

Statistics



Machine learning



Hello Machine ...

Let me show you some queries ...

Let me tell you the correct answers to those queries ...

Find the pattern!

Here are some queries that you haven't seen before.

Let me check how well you can answer those based on the pattern that you learned.

Sample

Fit the model

Quality of fit (within sample)

Out-of-sample prediction

Out-of-sample quality of fit

Training set

Train a model

Training accuracy

Test set

Test accuracy



# Linear regression





# Linear regression: sample / training set

Sample of size  $n$  is a set of  $n$  value pairs:

$$(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$$

We can the data in two vectors:

$$(x_1, x_2, \dots, x_n), (y_1, y_2, \dots, y_n)$$



# Linear regression: sample / training set

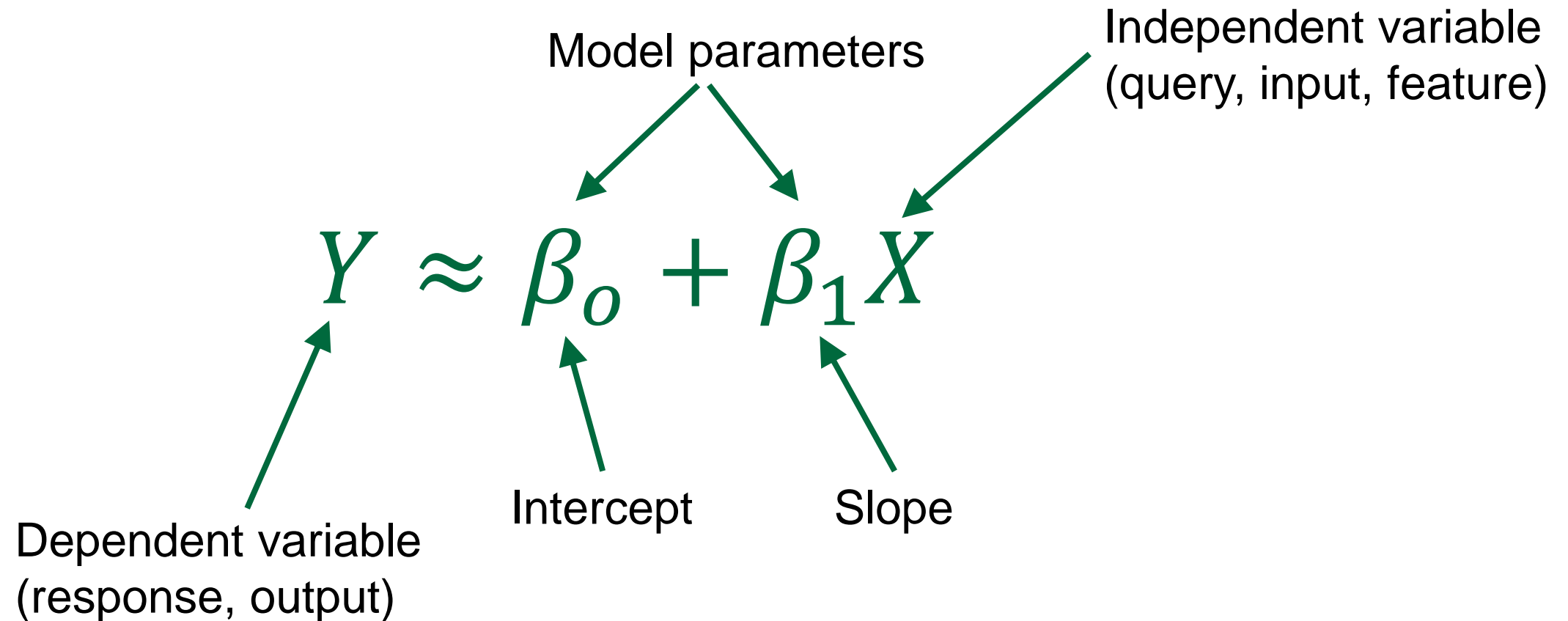
Sample of size  $n$  is a set of  $n$  value pairs:

$$(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$$

We can the data in two vectors:

$$(x_1, x_2, \dots, x_n), \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}$$

# Linear regression: the model



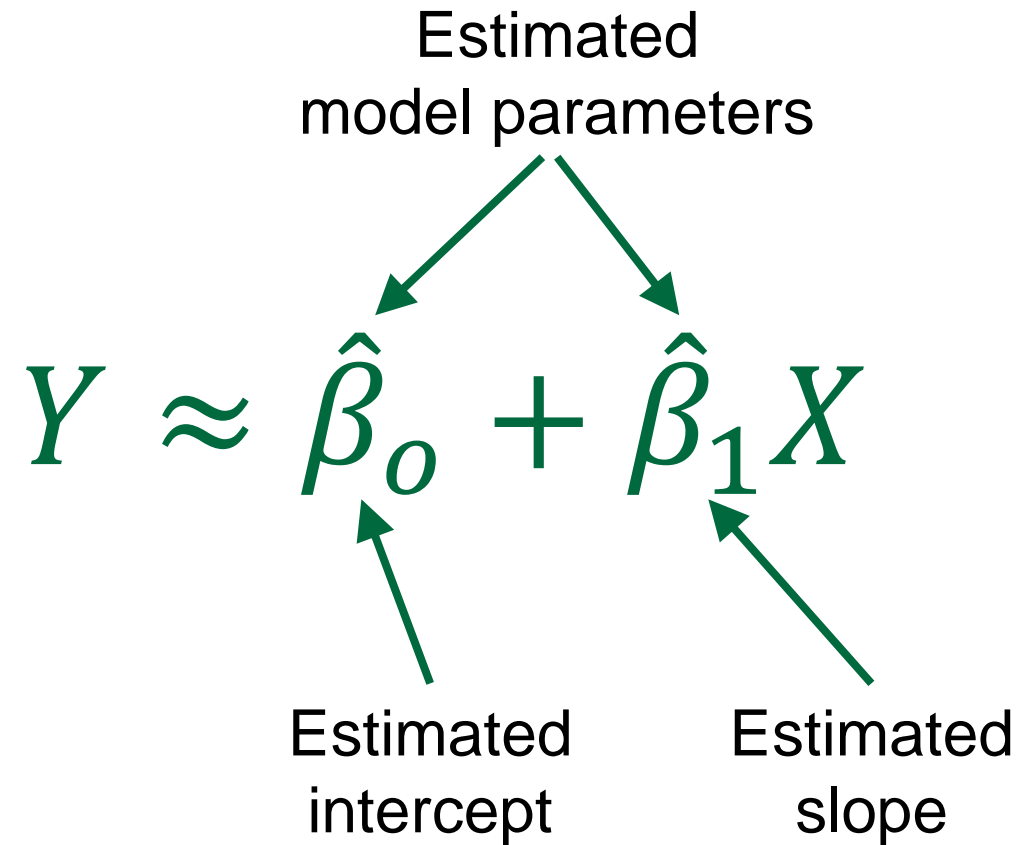
# Linear regression: fitting the model

Estimated  
model parameters

$$Y \approx \hat{\beta}_0 + \hat{\beta}_1 X$$

Estimated  
intercept

Estimated  
slope



Model parameters are unknown. Need to be estimated from data.

# Linear regression: fitting the model

In general, model fitting can involve:

- complex training algorithms
- many iterations of (re-)estimating model parameters and
- assessing the quality of fit to the training data.

Not for linear regression.

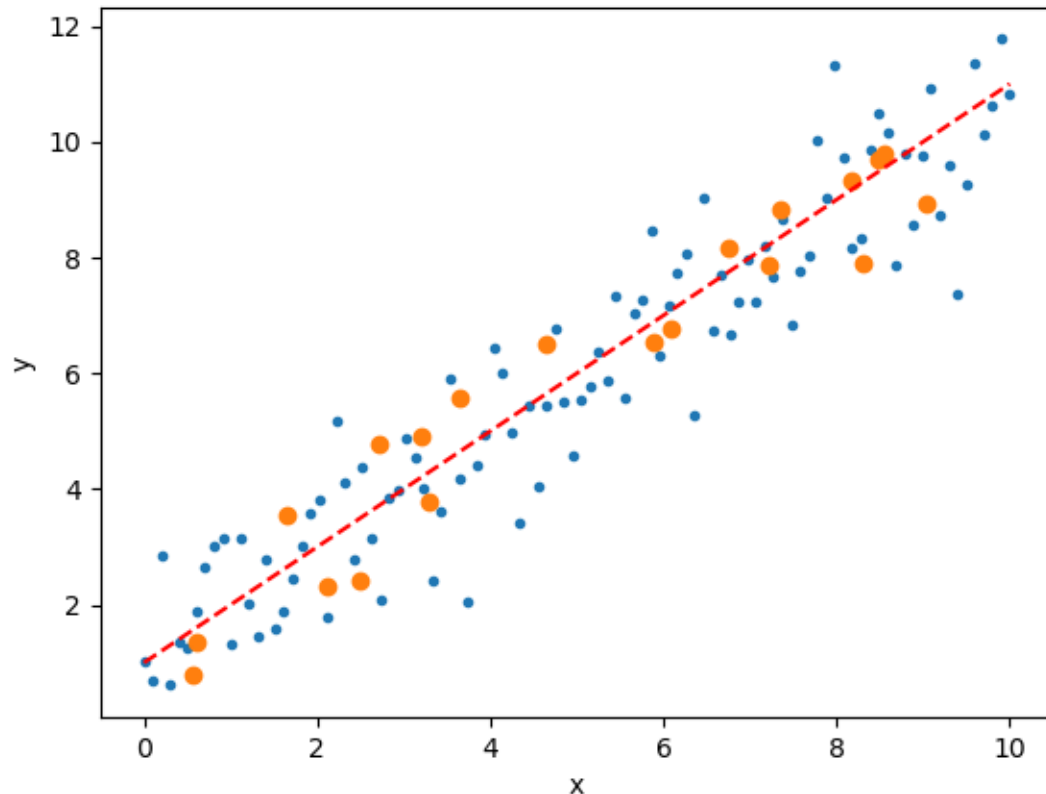
$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$



# Linear regression: Quality of fit

How well does our line fit the data?



Residual sum  
of squares (RSS)

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

RSS of  
constant  
model

# Linear regression: Quality of fit

Residual standard  
error (RSE)

$$RSE = \sqrt{\frac{RSS}{n-2}}$$

Mean squared  
error (MSE)

$$MSE = \frac{RSS}{n}$$

Residual sum  
of squares (RSS)

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

Fraction of  
variance  
explained  
compared  
to constant  
model

Total sum of  
squares (TSS)

$$TSS = \sum_{i=1}^n (\bar{y}_i - y_i)^2$$

Variance  
explained ( $R^2$ )

$$R^2 = \frac{TSS - RSS}{TSS}$$

account for  
sample size  
and “model  
complexity”

account for  
sample size



# Linear regression: quality of fit

What does it mean when the quality of fit is low?

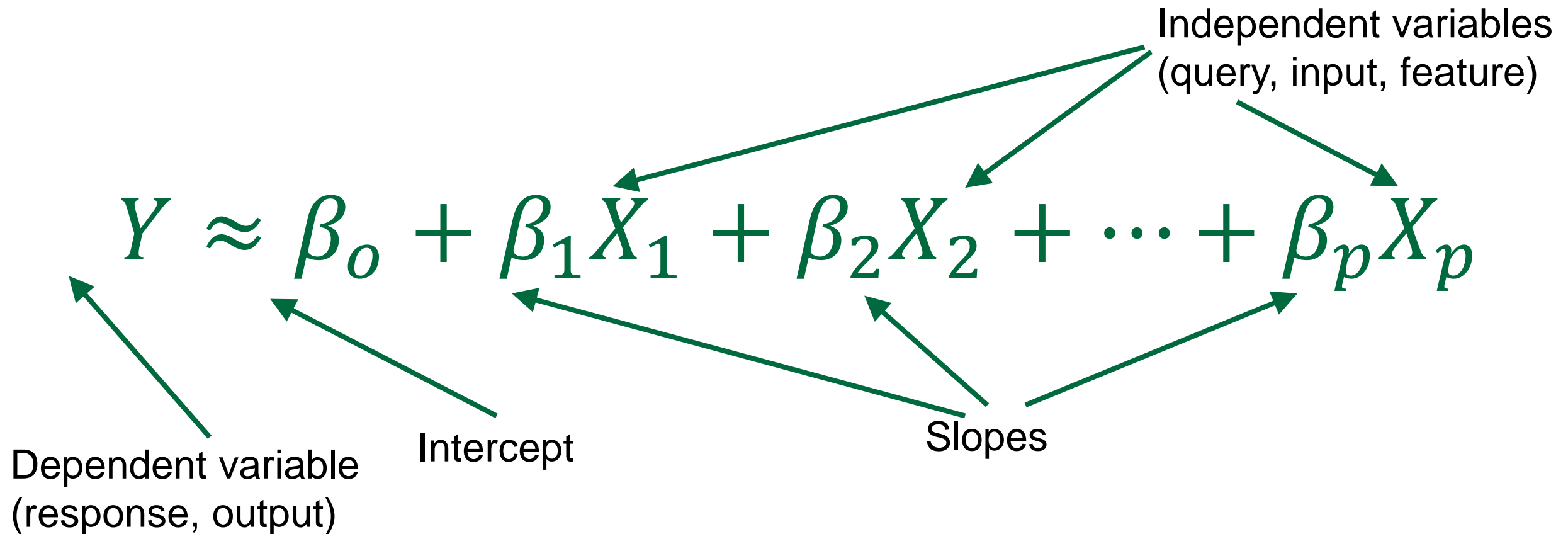
- Bad parameter estimation
  - not an issue for linear regression
- Relationship too weak or data set too small
  - check via significance test: t statistic, p value
- Bad model
  - e.g. “very” non-linear relationship between  $x$  and  $y$





# Multivariate linear regression

# Multivariate linear regression: the model





# Multivariate linear regression: fitting the model

$$Y \approx \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \cdots + \hat{\beta}_p X_p$$

Model parameters are unknown. Need to be estimated from data.

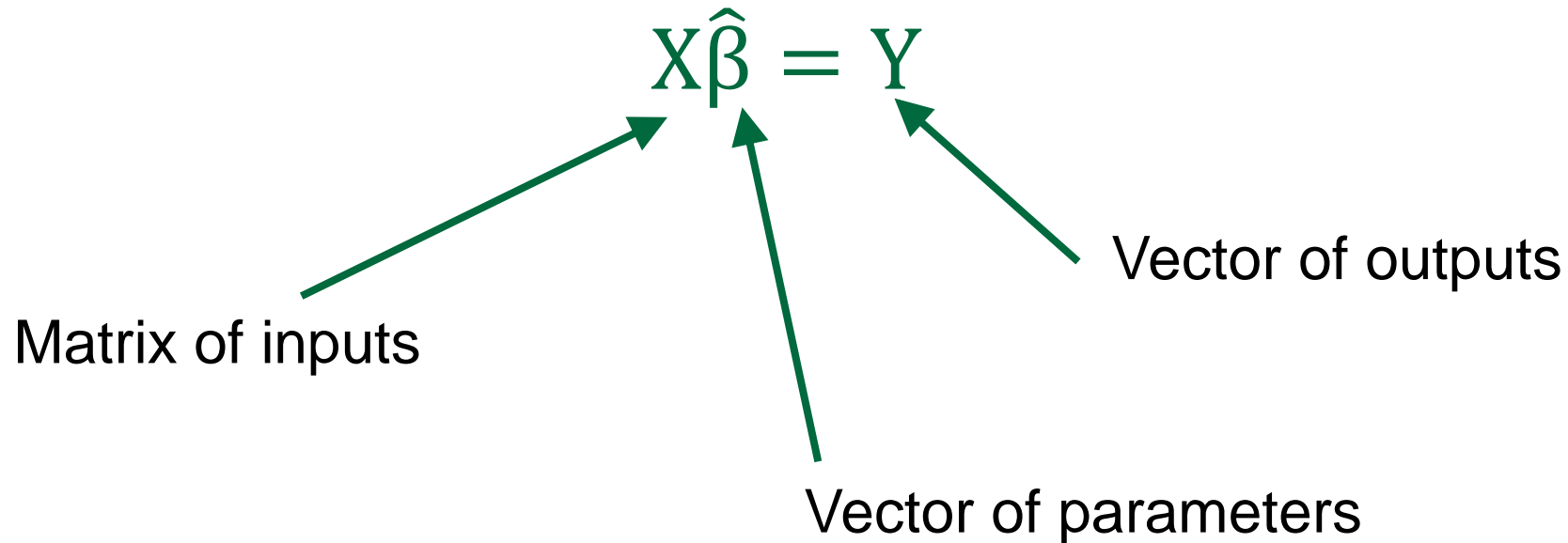
# Multivariate linear regression: fitting the model

For centered data:

$$\begin{pmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,p} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,p} \end{pmatrix} \begin{pmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \vdots \\ \hat{\beta}_p \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}$$

# Multivariate linear regression: fitting the model

For centered data:

$$X\hat{\beta} = Y$$


Matrix of inputs

Vector of parameters

Vector of outputs



# Strengths and limitations of linear regression



# Strengths

1. Simple model
2. Simple “training procedure”
3. “Convergence” guaranteed
4. Optimality guaranteed (see Gauss-Markov theorem)
5. Well-established quality of fit measures
6. Good starting point for regression problems



# Limitations

- Non-linearity of the response-predictor relationships
  - Residual plots can help identify non-linearity.
- Correlation of error terms
  - Can lead to inefficient estimates of the coefficients.
- Heteroscedasticity: Non-constant variance of error terms
  - violates the assumptions of the linear regression model.
- Outliers
  - Points that have a large influence on the fit of the model.
- Collinearity:
  - When predictor variables are highly correlated, it's difficult to separate out the individual effects of each predictor.