Multiple linear regression

Applied Data Science using R, Sessions 15 & 16

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Introduction

- Build upon the example from previous session: what are the determinants of beer consumption?
    - We considered two variables **separately**: income and beer price
- Multiple regression analysis allows us to consider **both variables at once**
    - This changes the interpretation of the obtained estimates
    - They now give the association with the outcome variable, assuming that all other variables are held constant

Goals for today

I. Learn how to implement and interpret multiple linear regression models

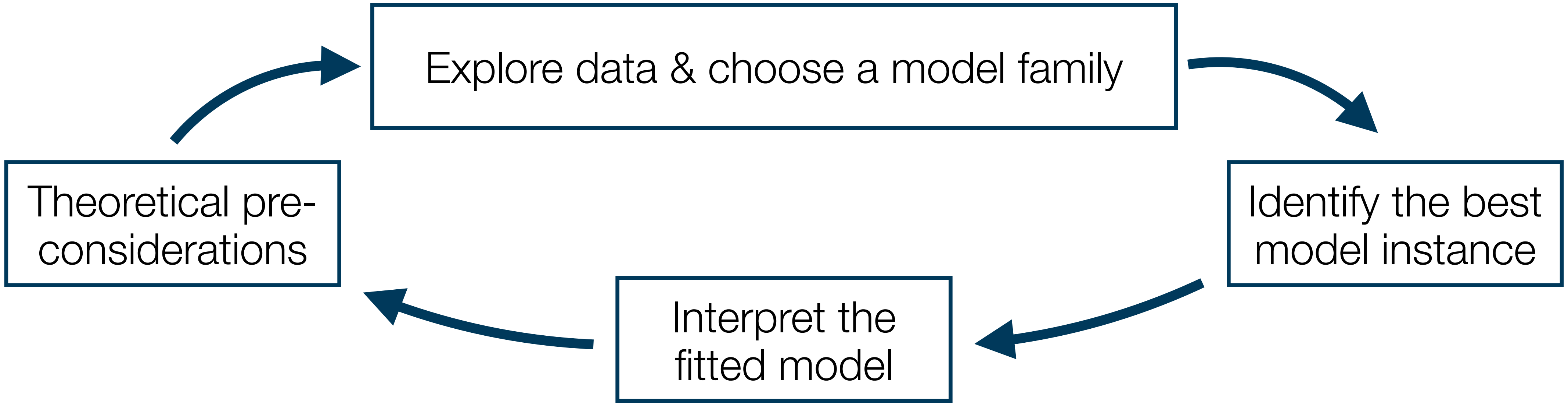
II. Learn how to deal with categorial variables within a regression

III. Understand the concept of interaction effect and the difference between interaction and parallel slopes models

Multiple linear Regression

Introduction

- In terms of theoretical background and technical implementation, multiple regression analysis is very similar to simple linear regression
- The overall sequence of considerations remains the same:

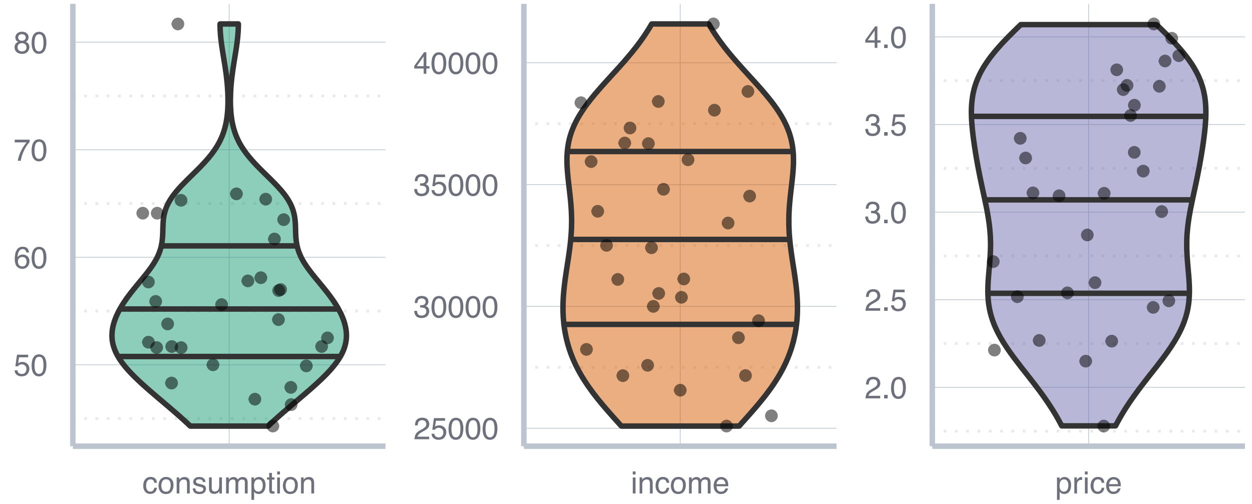


- Let us take this opportunity to recap what we have learned

Data exploration

- We again use the data set `DataScienceExercises::beer`, but only the three variables of interest

```
── Data Summary ────────────────────────
                           Values
Name                       beer_data
Number of rows             30
Number of columns          3
Key                        NULL
________________________
Column type frequency:
  numeric                  3
________________________
Group variables            None
```




```
── Variable type: numeric ──────────────────────────────────────────────────────
  skim_variable n_missing complete_rate    mean     sd    p0   p25   p50   p75
1 consumption           0             1    56.1   7.86  44.3  51.6  54.9  60.8
2 price                 0             1    3.08  0.642  1.78  2.53  3.11  3.68
3 income                0             1 32602.  4542.  25088 28888 32457 36516.
     p100 hist
1    81.7
2    4.07
3 41593
```

- Since `consumption`, `income` and `price` are all numerical, we can basically proceed as in the previous session

Data exploration

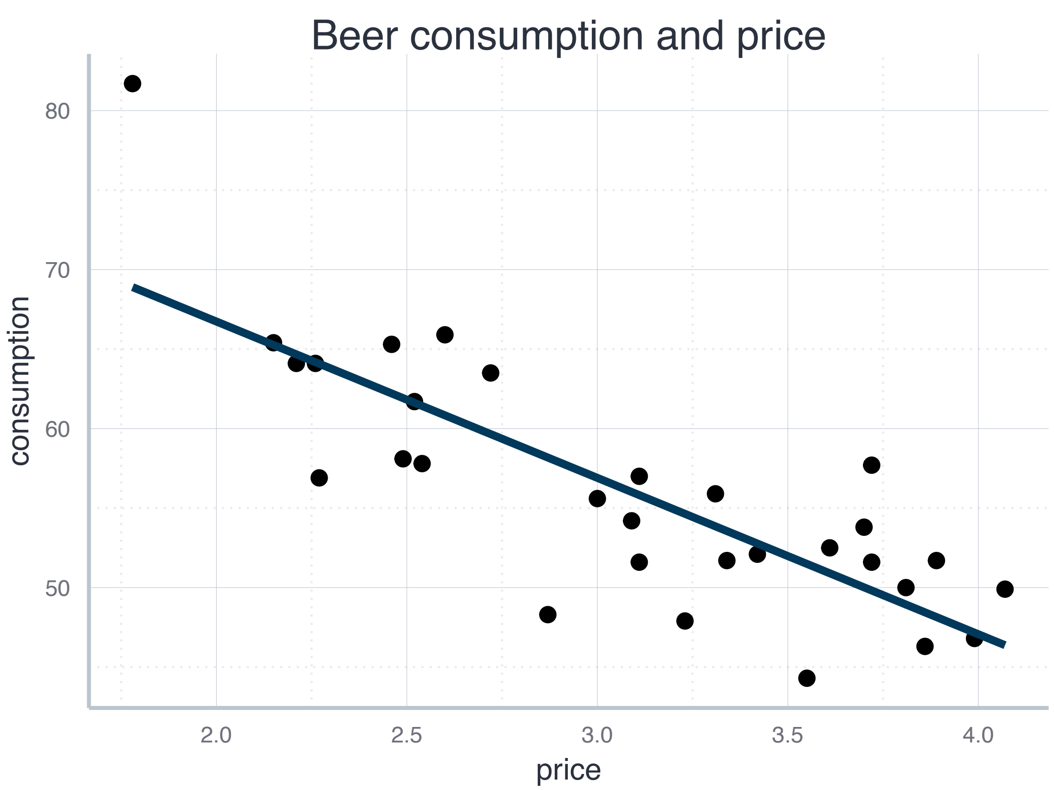
- Our focus on both income and price can be justified **theoretically** via reference to economic theory....
- ...and **empirically** by looking at the correlations:

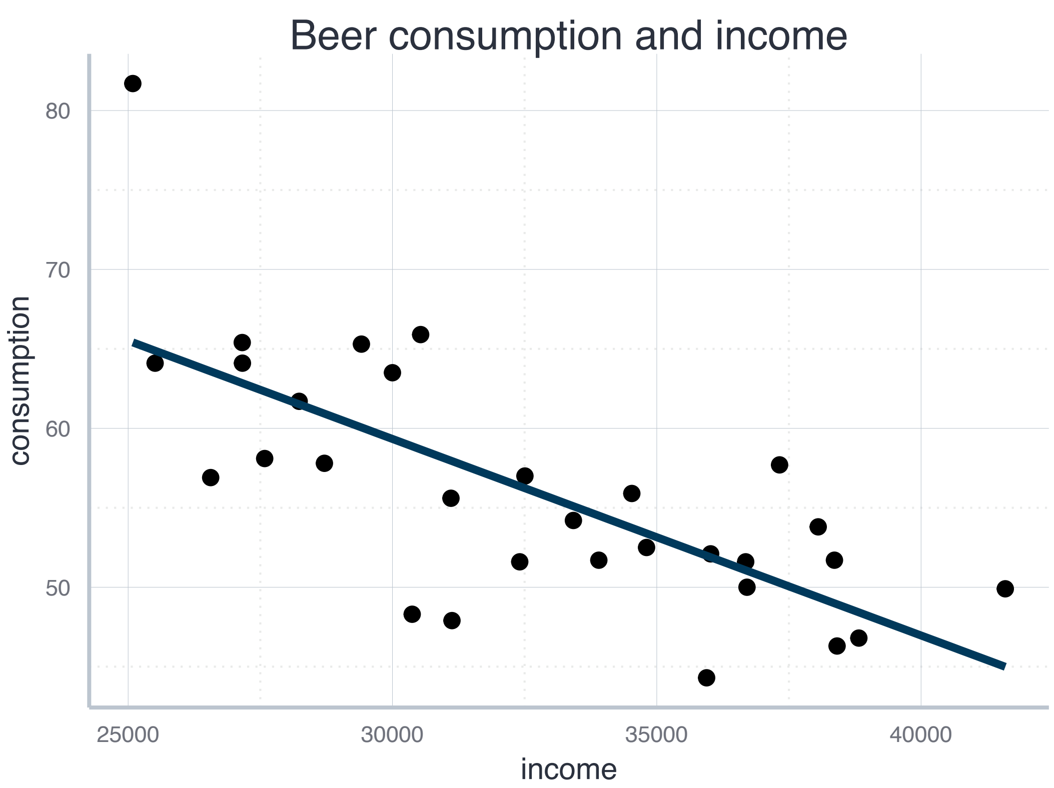
```
> cor(beer_data$consumption, beer_data$price)
[1] -0.8038513
> cor(beer_data$consumption, beer_data$income)
[1] -0.714995
> cor(beer_data)
            consumption      price     income
consumption   1.0000000 -0.8038513 -0.7149950
price        -0.8038513  1.0000000  0.9763155
income       -0.7149950  0.9763155  1.0000000
```

Note: very strong correlations between explanatory variables should be a warning sign! More on this later!

Data exploration

- Our focus on both income and price can be justified theoretically via reference to economic theory....
- ...and empirically by looking at the correlations:





➡ In both cases, a linear models seems to be an adequate choice!

Estimate a multiple regression model

- Writing down our regression model with two explanatory variables is very similar to the case with only one variable:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon$$

$$CONS = \beta_0 + \beta_1 PRICE + \beta_2 INCOME + \epsilon$$

- The computation in R is equally similar → here is the general form:

```
lm(y ~ x1 + x2, data=data_used)
```

- **Exercise**: adjust the code to the actual data set and estimate the model!

Interpret a multiple regression model

```
> cons_model <- lm(consumption ~ price + income, data = beer_data)
> moderndive::get_regression_table(cons_model)
# A tibble: 3 × 7
  term      estimate std_error statistic p_value lower_ci upper_ci
  <chr>        <dbl>     <dbl>     <dbl>   <dbl>    <dbl>    <dbl>
1 intercept   57.2       9.47       6.04   0         37.7     76.6
2 price      -27.7       5.44      -5.08   0        -38.8    -16.5
3 income       0.003     0.001      3.36   0.002      0.001    0.004
```

- In the multiple case, the coefficients must be interpreted in a *ceteris paribus* fashion:

For every increase of 1 unit in `price`, there is an associated decrease of, on average **and ceteris paribus**, 27.7 units of `consumption`.

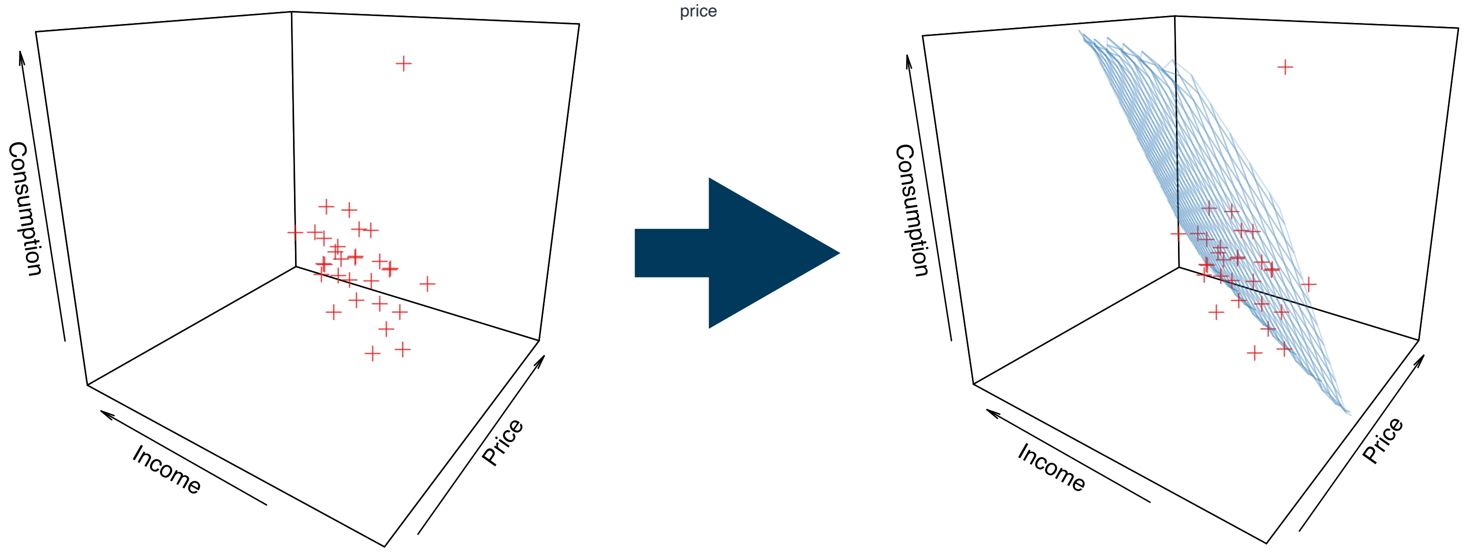
For every increase of 1 unit in `income`, there is an associated decrease of, on average **and ceteris paribus**, 0.003 units of `consumption`.

Graphical interpretation

- The more explanatory variables you use, the more difficult it becomes to think about the regression problem graphically

- In the simple regression case we fitted a regression line

- In the case of two explanatory variables we fit a regression plane



- In cases with more than two variables we fit a regression hyperplane

- But this is not easy to get your head around → if anything plot conditional relationships (see optional tutorial on the course page)

Outlook: the choice of variables matters

- **Guess:** how do the estimates for income and price from the simple regression models and the multiple regression model relate to each other?

	Model 1	Model 2	Model 3
(Intercept)	86.406 ***	96.439 ***	57.160 ***
	(4.324)	(7.521)	(9.468)
price	-9.835 ***		-27.653 ***
	(1.375)		(5.438)
income		-0.001 ***	0.003 **
		(0.000)	(0.001)
R^2	0.646	0.511	0.750
Adj. R^2	0.634	0.494	0.732
Num. obs.	30	30	30

- This points to an important concept: **omitted variable bias**
  - When you forget one important variable in your model, all resulting estimates can be misleading → more on this in later sessions

Exercise

- Get together in groups and use again the data on beer consumption
- But this time use all potential explanatory variables for the RHS:
    - `price`: the price for beer
    - `price_liquor`: the price for other strong alcoholic beverages
    - `price_other`: price of other goods and services
    - `income`: household income
- Before you do the estimation, what would you expect regarding their effect?
- How can you interpret the estimates you obtained? How did the estimates change over different specifications?
- What specification would you prefer? Why?

Categorial variables: Simple regression

Using categorical variables

- So far we only worked with numerical and continuous variables
    - Income, prices, consumption,...
- But there are other types of variables, e.g. categorial data
    - Gender, continent of origin, employment status,...
- In the following we want to learn how to consider categorial data as **explanatory variables**
    - If you have categorial variables on the LHS → different estimation methods
- Let us illustrate the procedure using the data on life expectancy, but focus on the role of different continents
    - Data: `DataScienceExercises::gdplifexp2007`
    - Variables of interest: `continent`, `lifeExp`, and `gdpPercap`

Exploratory analysis

```
── Data Summary ────────────────────────
                           Values
Name                       life_exp
Number of rows             142
Number of columns          3
Key                        NULL
_______________________
Column type frequency:
  factor                   1
  numeric                  2
________________________
Group variables            None

── Variable type: factor ──────────────────────────────────────────────────────────
  skim_variable n_missing complete_rate ordered n_unique top_counts
1 continent             0             1 FALSE          5 Afr: 52, Asi: 33, Eur: 30, Ame: 25

── Variable type: numeric ─────────────────────────────────────────────────────────
  skim_variable n_missing complete_rate   mean     sd    p0    p25   p50   p75   p100 hist
1 lifeExp               0             1   67.0   12.1  39.6   57.2  71.9  76.4   82.6 ▁▁▂▃▇
2 gdpPercap             0             1 11680. 12860.  278.  1625. 6124. 18009. 49357. ▇▁▁▁▁
```

No problems with missing data, 142 observations in total

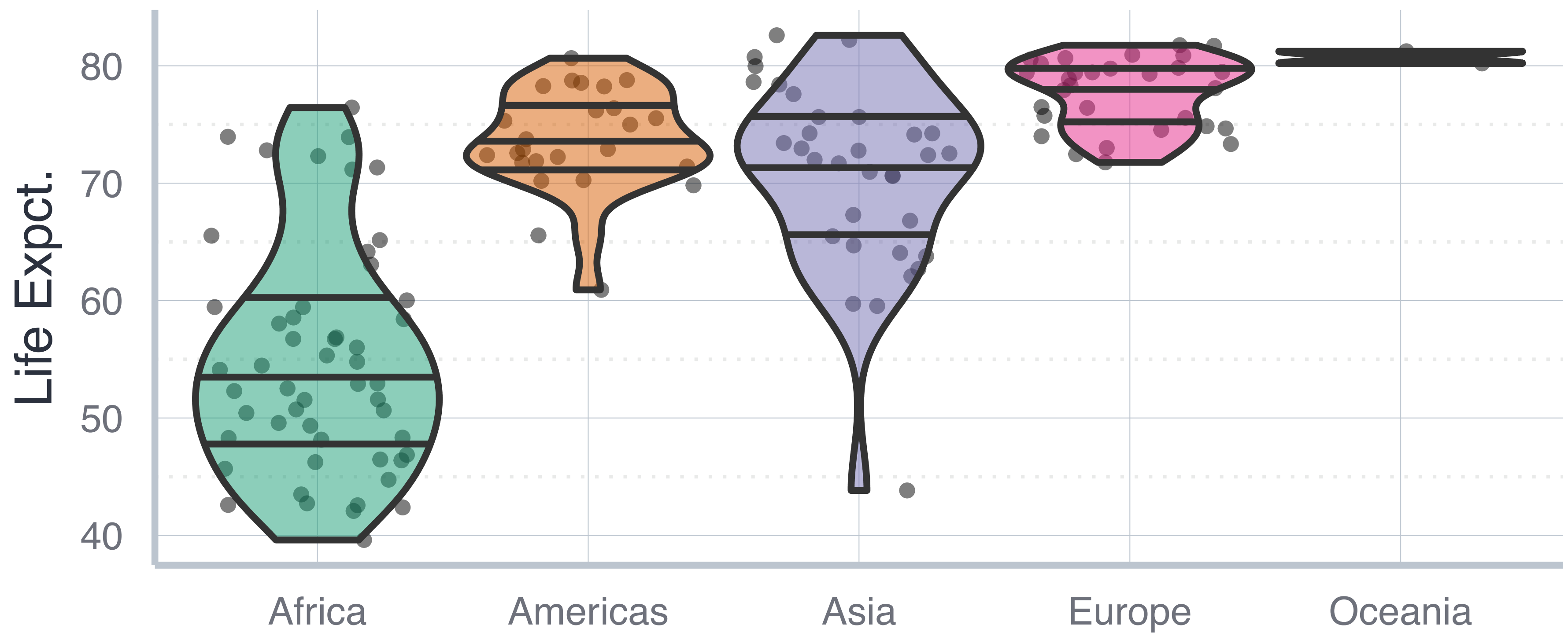
There are five different continents with Africa comprising most countries (52)

Mean and median differ considerable due to skewed distribution of the variables!

- Note: `continent` was saved as `character`, but we transformed it into `factor`

Exploratory analysis

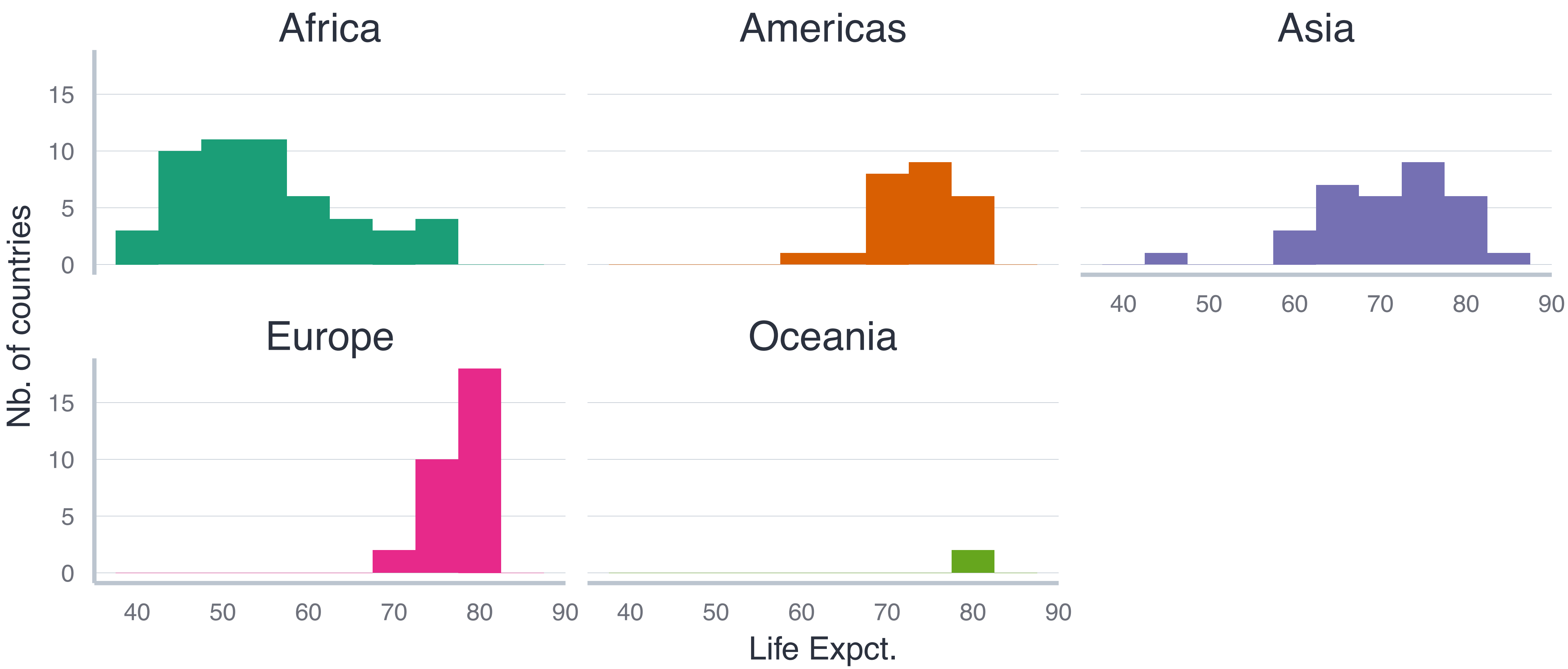
- We see considerable differences also within continents:



- Especially Oceania will be hard to interpret since it comprises only two countries

Exploratory analysis

- To look at the distribution within countries, histograms are also useful:



- For categorial variables, fitting a regression line has a different meaning

Fitting a model with categorical variables

- The notation for a model with a categorical variable on the RHS is similar...
    - ...but the technical implementation is quite different
- While we write:

$$lifeExp = \beta_0 + \beta_1 \cdot CONT + \epsilon$$

- What actually being estimated is:

$$lifeExp = \beta_0 + \beta_{Am.} \cdot \mathbb{1}_{Am.}CONT + \beta_{As.} \cdot \mathbb{1}_{As.}CONT + \beta_{Eu.} \cdot \mathbb{1}_{Eu.}CONT + \beta_{Oc.} \cdot \mathbb{1}_{Oc.}CONT + \epsilon$$

- Here $\mathbb{1}_x(X)$ is an **indicator function** that takes the value 1 if $X = x$ and zero otherwise
    - Thus $\mathbb{1}_{Am.}(CONT) = 1$ iff $CONT$ equals $Am.$ (i.e. Americas), and 0 otherwise
    - Note that there are four indicator functions → four continents (plus one as a baseline level)
- The estimates must, therefore, always be interpreted against a baseline value (here: the first factor level, i.e. Africa)

Interpreting a model with categorical variables

$$lifeExp = \beta_0 + \beta_{Am.} \cdot \mathbb{1}_{Am.}CONT + \beta_{As.} \cdot \mathbb{1}_{As.}CONT + \beta_{Eu.} \cdot \mathbb{1}_{Eu.}CONT + \beta_{Oc.} \cdot \mathbb{1}_{Oc.}CONT + \epsilon$$

- Lets consider the results from estimating this formula one by one:
  - Note that the code for the regression remains `lm(lifeExp~continent)`

```
> cont_linmod <- lm(lifeExp~continent, data = life_exp)
> get_regression_table(cont_linmod)
# A tibble: 5 × 7
  term                  estimate
  <chr>                    <dbl>
1 intercept                 54.8
2 continent: Americas       18.8
3 continent: Asia           15.9
4 continent: Europe         22.8
5 continent: Oceania        25.9
```

	continent	lifeExp_mean	diff_africa
	<fct>	<dbl>	<dbl>
1	Africa	54.8	0
2	Americas	73.6	18.8
3	Asia	70.7	15.9
4	Europe	77.6	22.8
5	Oceania	80.7	25.9

- The intercept corresponds to the mean value of the baseline category
  - The other estimates correspond to the deviation of the group mean from this baseline

Interpreting a model with categorical variables

$$lifeExp = \beta_0 + \beta_{Am.} \cdot \mathbb{I}_{Am.}CONT + \beta_{As.} \cdot \mathbb{I}_{As.}CONT + \beta_{Eu.} \cdot \mathbb{I}_{Eu.}CONT + \beta_{Oc.} \cdot \mathbb{I}_{Oc.}CONT + \epsilon$$

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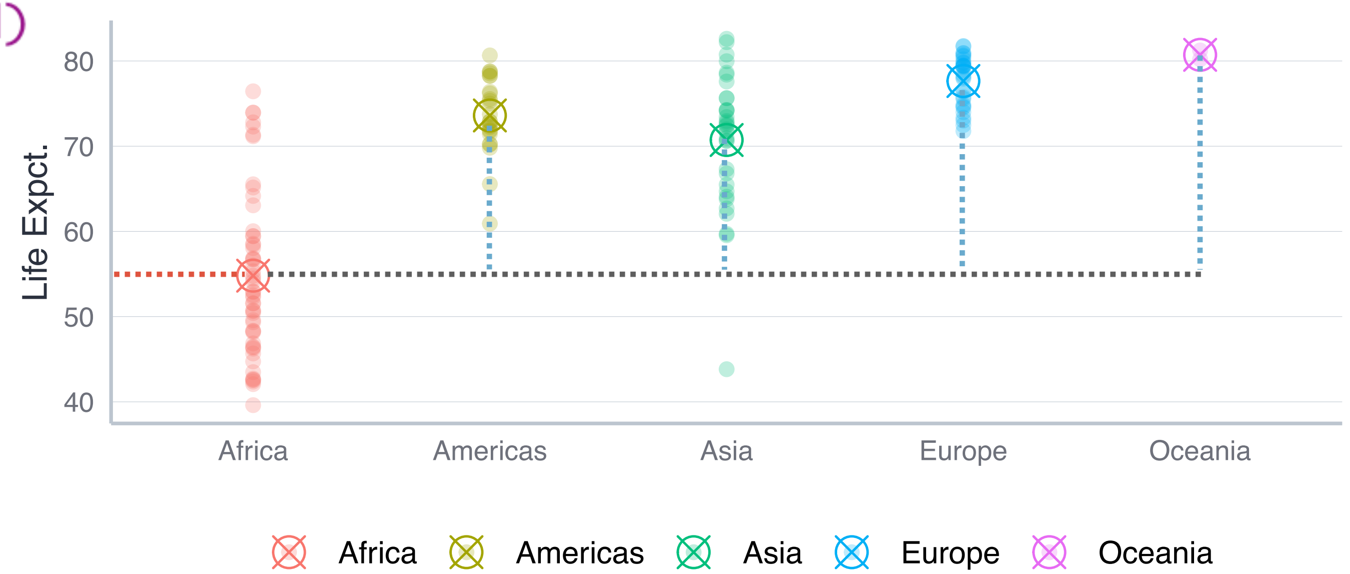


- The intercept corresponds to the mean value of the baseline category
  - The other estimates correspond to the deviation of the group mean from this baseline

Quick recap

- The result of the following regression model...

$$SUGAR = \beta_0 + \beta_1 KIND + \epsilon$$

```
lm(`residual sugar` ~ kind, data = wine_data)
```

- ...is as follows:

term	estimate
<chr>	<dbl>
intercept	2.54
kind: white	3.85

- The variables are as follows:
  - `` `residual sugar` ``: the amount of sugar left in the wine
  - `kind`: the kind of wine, red or white

- How would you interpret the estimated coefficients?

Categorical variables: Multiple regression

Introduction

- What if we would like to consider both continuous and categorical variables?
- In this case we must distinguish two cases: an **interaction model**, and a **parallel slope model**
  - Note: both also occur in the case without categorical variables, but here the distinction is most intuitive
- To illustrate the difference, we consider a data set on the prices of economics journals: `DataScienceExercises::econjournals`
  - Only consider journals that published at least 10 papers and cost under 5000 USD per year: `dplyr::filter(papers>10, sub_price<5000)`
- **Main interest:** what is the impact of the paper length on the subscription price? Are there differences between profit and nonprofit publishers?

The parallel slopes model

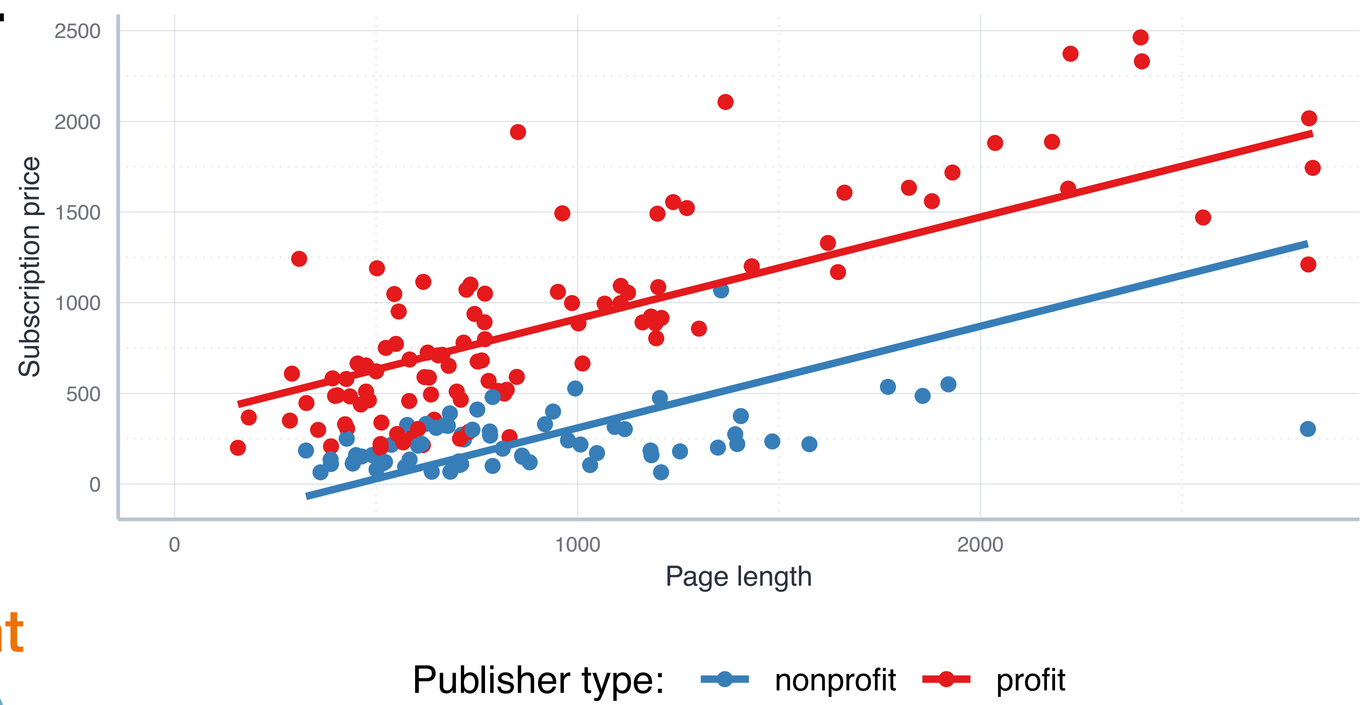
- The variables `pages_py` and `sub_price` are continuous, the variable `publisher_type` is categorical

- What if we simple add both explanatory variables to the RHS?

```
lm(sub_price~pages_py+publisher_type)
```

- Lets look at the resulting estimates:

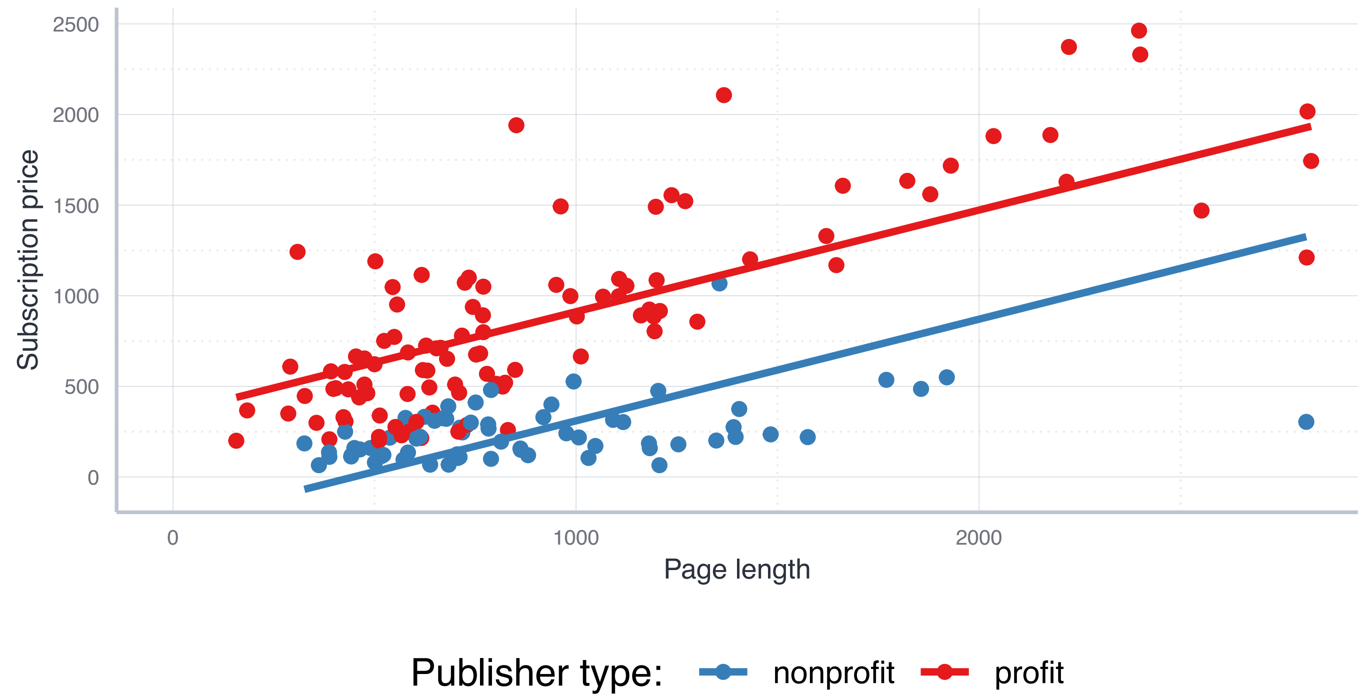
	term	estimate
	<chr>	<dbl>
1	intercept	-251.
2	pages_py	0.561
3	publisher_type: profit	602.



The categorical variables correspond to different intercepts, but each group has the same slope

The parallel slopes model

- The results of the parallel slopes model are intuitive in the sense that journals from non-profit publishers are cheaper
- The model suggests, however, that an additional page comes with the same increase in journal price
- The visual inspection, however, indicates that this relationship differs across group



	term	estimate
	<chr>	<dbl>
1	intercept	-251.
2	pages_py	0.561
3	publisher_type: profit	602.

To capture the idea that the association between page length and price differs across groups we need an **interaction model**

The interaction model

- This model is more complex: it does not assume that sloper are the same in the different groups → variables interact with each other

- Technically, we just replace the + by an * in our model formula:

```
lm(sub_price~pages_py*publisher_type)
```

```
term                           estimate
<chr>                             <dbl>
intercept                        111.
pages_py                           0.154
publisher_type: profit           111.
pages_py:publisher_typeprofit      0.543
```

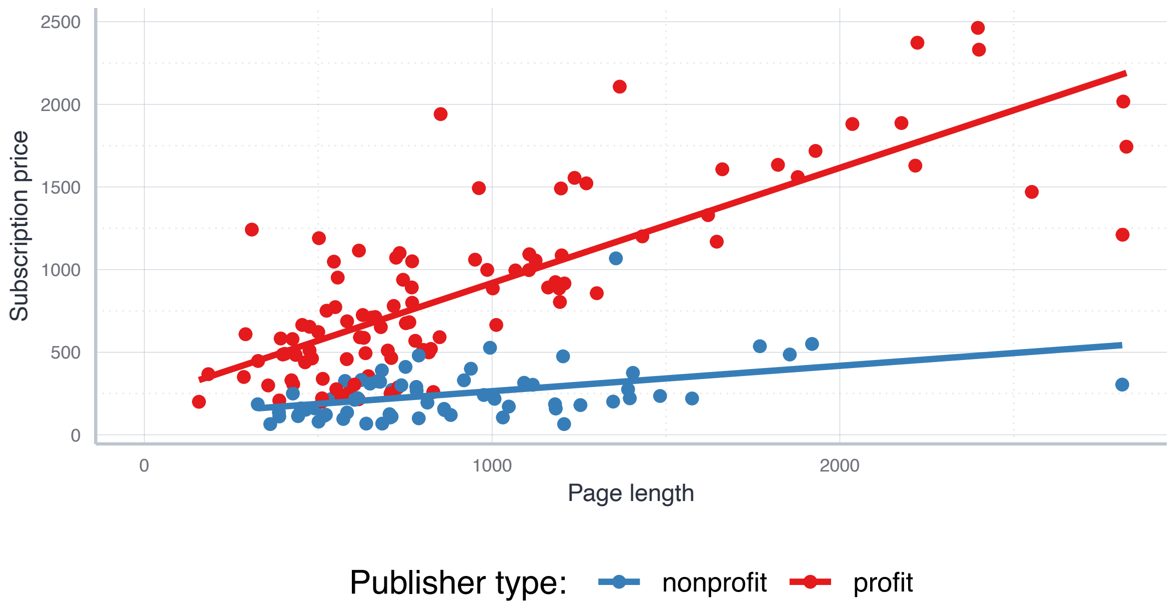
- There is one more parameter to estimate than in the PSM

- But the plot suggests that this additional complexity is warranted: for-profit publisher charge more per additional page

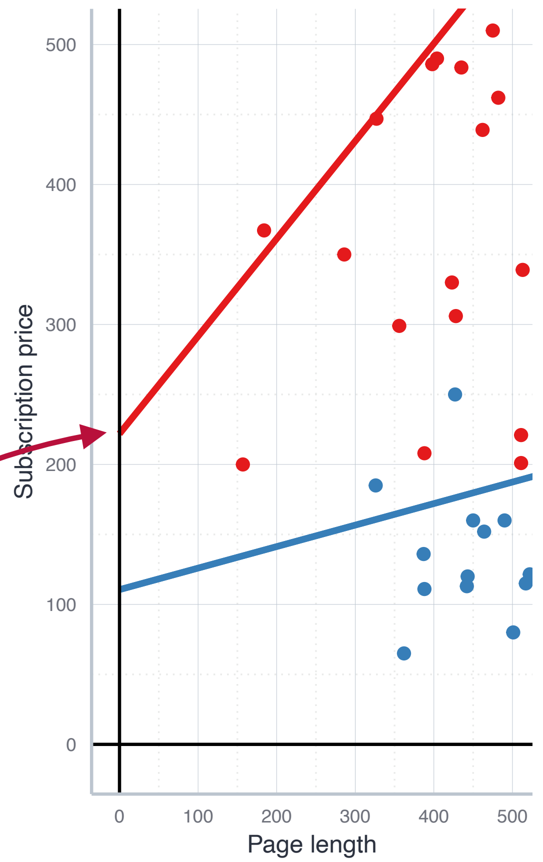
The interaction model

Interpretation

```
term                         estimate
<chr>                           <dbl>
intercept                      111.
pages_py                         0.154
publisher_type: profit         111.
pages_py:publisher_typeprofit    0.543
```

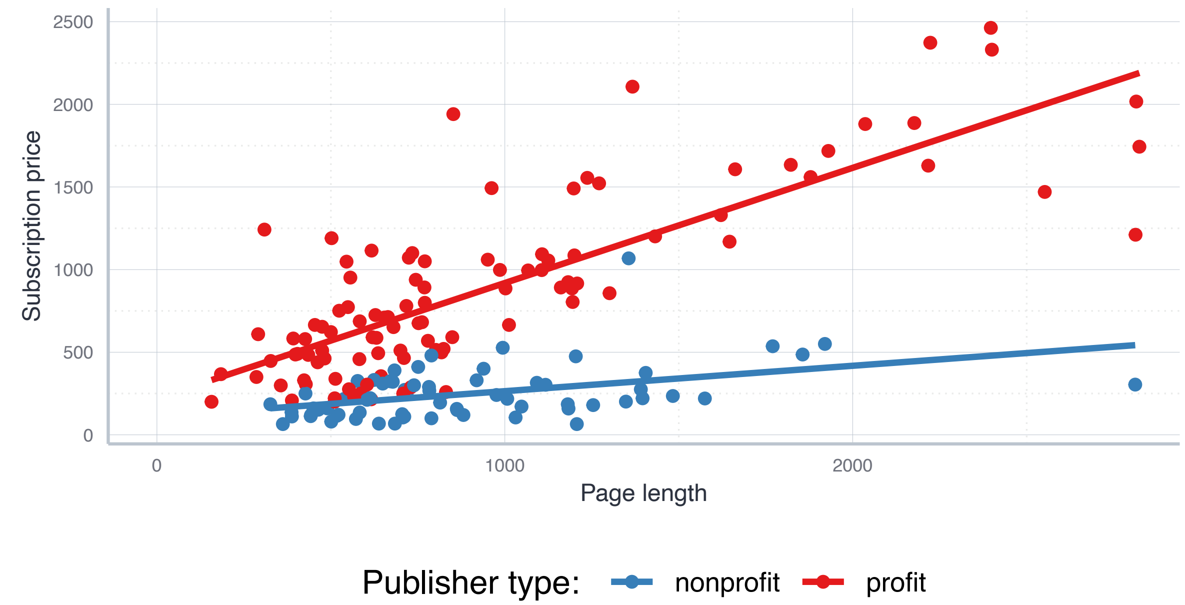


- The estimate **`intercept`** is the intercept only for the reference group → 111
- The estimate **`pages_py`** gives the slope only for the reference group → 0.154
- The estimate **`publisher_type:profit`** gives the difference in the intercept for the profit group
  - `intercept + publisher_type:profit = 222`

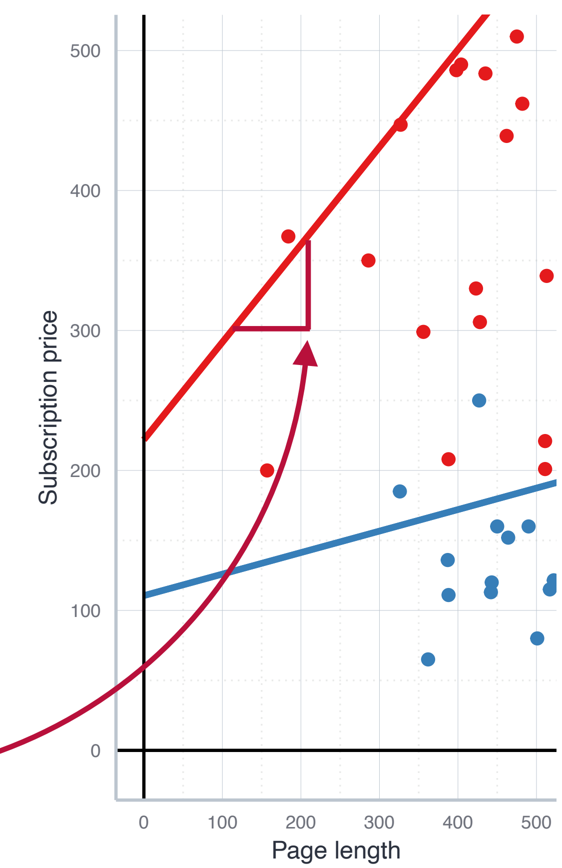


The interaction model
Interpretation

```
term                               estimate
<chr>                                 <dbl>
intercept                           111.
pages_py                              0.154
publisher_type: profit              111.
pages_py:publisher_typeprofit         0.543
```



- The estimate **`intercept`** is the intercept only for the reference group → 111
- The estimate **`pages_py`** gives the slope only for the reference group → 0.154
- The estimate **`pages_py:profit`** gives the difference in the slope for the profit group
  - `pages_py+pages_py:publisher_typeprofit=0.697`



The interaction and parallel slopes model

	term	estimate
	<chr>	<dbl>
1	intercept	-251.
2	pages_py	0.561
3	publisher_type: profit	602.

term	estimate
<chr>	<dbl>
intercept	111.
pages_py	0.154
publisher_type: profit	111.
pages_py:publisher_typeprofit	0.543

- As a general rule of thumb: the PSM is better if nothing suggests that slopes differ → then the estimation is more efficient
  - In other cases, its safer to use the interaction mode
  - We learn how to test for the right model in later sessions

Model selection in the multiple variable case

Model selection using R^2

- You can use R^2 as one argument for model selection, i.e. when you need to decide which models works best for your purpose at hand
- Compare, for instance, the R^2 of the PSM and interaction model we estimated before:
- `summary(journal_linmod_intct)[["r.squared"]]`: 0.75
- `summary(journal_linmod_psm)[["r.squared"]]`: 0.68
- The reference to R^2 confirms our impression that the more complex interaction model is warranted
- But: using R^2 in the multiple regression context can be misleading: adding more variables typically increases the R^2 for purely mathematical reasons

Model selection using R^2

- To see why consider the formal definition of R^2:

$$R^2 = \frac{ESS}{TSS} = \frac{\sum_{i=1}^{N} \left(\hat{y}_i - \bar{y}\right)}{\sum_{i=1}^{N} \left(y_i - \bar{y}\right)}$$

  - An additional explanatory variable never changes TSS, but mostly increases ESS at least a bit → bias towards 'too complex' models

- There is an alternative, the adjusted R^2, denoted as $\bar{R}^2$:

$$\bar{R}^2 = 1 - \frac{\sum_{i=1}^{n} e^2/(N-K-1)}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2/(N-1)}$$

  - Here, N is the number of observations and K die Anzahl der zu schätzenden Parameter

Model selection using R^2

- $\bar{R}^2$ only increases if the additional variables contribute to the explanatory power for substantial reasons
  - Drawback: we cannot interpret its value as the share of explained variation any more
- As we learn later, both R^2 and $\bar{R}^2$ provide valuable information, but they should be complemented by other diagnostic tools
- In the present PSM vs. IM case, using $\bar{R}^2$ instead of R^2 does not alter the conclusion, but you find plenty other examples in the readings

Summary & outlook

Summary

- We extended the simple to the multiple regression model
- This allows us to have more than one variable on the RHS
- The interpretation of the estimates is different:
  - For every increase of 1 unit in the explanatory variable i, there is an associated decrease of, on average **and ceteris paribus**, of $\hat{\beta}_i$ units in the response
  - Ceteris paribus: holding all other variables constant
- This allows us to separate the variation in the response variable according to the different explanatory variables
- Forgetting relevant explanatory variables seems to cause problems since adding a variable changes estimates of all other variables

Summary

- We also learned about how to include categorical variables to regressions
- Technically this is easy, but the interpretation becomes a bit trickier
- When both continuous and categorical variables are used, we learner about the difference between interaction and parallel slope models
- The latter are simpler, but often the complexity of the former model is warranted
- Finally, we saw that selecting models using R^2 requires a bit more caution in the multiple regression context

Outlook

- Next session we lay the ground for a more nuanced analysis of our model by introducing **sampling theory**
  - How to make statement about populations from which we draw samples?
  - Whenever we want to make such generalisations or predict something with our model, sampling theory is key!

Tasks until next time:

1. Fill in the **quick feedback survey** on Moodle
2. Read the **tutorials** posted on the course page
3. Do the **exercises** provided on the course page and **discuss problems** and difficulties via the Moodle forum