

Plan for today

Why go beyond the linear regression (OLS)?

Structure of the class

Statistical models beyond linear regression

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02 februar 2026

Plan for today

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1st hour

- ▶ why you should care about our topic
- ▶ practicalities:
 - ▶ how we work
 - ▶ the exam

2nd hour

- ▶ intro to R, our statistics program

Why go beyond the linear regression (OLS)?

Assumptions of the linear model

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Linear models (OLS) rely on two assumptions that are often violated

- ▶ outcomes are continuous and unbounded
- ▶ observations are independent and identically distributed (iid)

⇒ *this class: alternative models when these are not satisfied.*

Our research topics don't fit the OLS

- ▶ **Most phenomena in political science are not continuous**
 - ▶ (re)election, vote choice, degree of satisfaction, civil war, difficulty of negotiations, labor force participation...
- ▶ **... nor are they independent of each other**
 - ▶ same MP has an increased probability of reelection in several elections
 - ▶ several civil wars happen in the same country

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Assumption 1: continuous and unbounded outcomes

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Outcomes are continuous and unbounded (“asymptotic”)

- ▶ political science theories imply a relationship between two phenomena: x and y
 - ▶ $y = \alpha + \beta x$
- ▶ for each unit increase in x , y increases with β units

\Rightarrow *this relationship is linear*

Violations of assumption 1

What happens if. . .

- ▶ β has digits, while y does not?
- ▶ x increases so that we pass what is feasible for y ?
- ▶ the relationship between x and y is not linear?

Example: Outcome is continuous, but predictions unrealistic

- ▶ Theory: We may model life expectancy as a function of income:
 $age = \alpha + \beta * income$
- ▶ Data:

age (y)	income (x)
0	0
50	50.000
?	200.000

- ▶ Results: $age = 0 + 0.001 * income$
- ▶ Prediction (scenario): $200 = 0 + 0.001 * 200.000$

What is the problem?

Predictions are unrealistic because the relationship between x and y is not linear

▶ **Why is this a problem?**

- ▶ predictions are wrong (least of our problems)
- ▶ β is wrong (kind of sad)
- ▶ standard error is wrong (catastrophy!)

▶ **How do we fix it?**

- ▶ we can recode x : e.g. log-transformation, truncation, etc.
- ▶ we can recode y
- ▶ we can recode y and its relationship with $x \rightarrow$ *generalized linear models* (GLMs)

Our research strategy: GLMs

- ▶ **The model we choose depends on**

- ▶ the “data generating process” (probability distribution)
- ▶ the measurement-level of the dependent variable (a mental short-cut)

- ▶ **The GLM does:**

- ▶ a recoding of the dependent variable to become continuous and unbounded
- ▶ draws from a probability distribution

⇒ *We end up with a linear statistical relationship*

Examples

Prospecting for relevant models often looks something like this

Theoretical concept	Operationalization	Measurement level	Model choice
(re)election	are MPs in period 1 observed in period 2?	binary	logit
vote choice	party names	categorical	multinomial
degree of satisfaction	dissatisfied, OK, satisfied...	ordinal	ordered
civil war	# of dead people	count	poisson
difficulty of negotiations	length of proceedings	# days to conclusion	event-history
labor force participation	time to employment	# days in unemployment	event-history

Your turn

What kind of phenomenon are you interested in for your BA/MA/secured dreams?

- ▶ your name
- ▶ your topic

Assumptions of the linear model (recap)

Linear models (OLS) rely on two assumptions that are often violated

- ▶ outcomes are continuous and unbounded
- ▶ **observations are independent and identically distributed (iid)**

Assumption 2: observations are iid

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Observations are independent and identically distributed (iid)

- ▶ **independent**

- ▶ the probability of observing one unit is not dependent on observing another

- ▶ **identically distributed:**

- ▶ they come from the same *probability distribution*:
- ▶ describes the *data generating process*
 - ▶ the shape of the relationship between x and y
 - ▶ the probability of an event (e.g. standard error)

Independent observations

Observations are not independent when they share characteristics (x) that may affect the outcome (y)

- ▶ missing data: may lead to a biased sample
- ▶ nested data: observations are correlated

⇒ *our β and standard error might be wrong*

Missing data

When we lack observations, and these observations are non-random, our sample is not representative

▶ Diagnostics of problem

- ▶ Missing completely at random (MCAR): absence is not related to the observation
- ▶ Missing at random (MAR): absence is related to observation, but not outcome
- ▶ Missing not at random (MNAR): absence is related to observation + outcome → *problem!*

▶ Solving the problem:

- ▶ Collect the data? Ignore it?
- ▶ Impute the data?

⇒ *last topic in the class*

Nested observations

We have nested observations when they belong to a group/share features

- ▶ e.g.: any panel data, civil wars in country, job-seekers in a locality, MPs in parties/committees/legislative periods. . .
- ▶ shared variation on x : a way to cluster standard errors
- ▶ relation to y : controlling for unobserved confounders

⇒ *some resemblance with MAR/MNAR*

GLMs in context

GLMs in context

There are other ways to approach statistics than what we will learn here:

- ▶ y-centred approaches
- ▶ x-centred approaches

⇒ ... *but regressions remain the bread and butter of statistical analysis*

Y-centred/prediction approaches

Some statistical models are primarily predictive or descriptive

- ▶ machine learning: aim to predict outcomes at all costs
- ▶ text analysis: categorizations, scaling. . .
- ▶ network analysis: description of networks

What's in it for us?

- ▶ often use GLMs “under the hood”
- ▶ create variables we can use in a regression

X-centred/causal inference approaches

Some statistical models are geared to make a causal claim

- ▶ rely on one or two linear models:
 - ▶ diff-in-diff, RDD, matching + OLS
 - ▶ instrumental variable/ fuzzy RDD
- ▶ focus on theory; statistics are often very simple

What's in it for us?

- ▶ understanding regressions helps us understand causal inference
- ▶ often very narrow applicability

Structure of the class

Flow

Flow

We will progress through the semester in cycles

- ▶ We start with 3 calm weeks (learn R), then pick up pace (learn models)
- ▶ 1-2-week cycle with two sessions per week:
 - ▶ seminar 1: lecture + reading
 - ▶ seminar 2: theory recap (student presentation) + seminar
- ▶ Final portfolio due end of May

Aim for the class

No magic, just work hours

My aim is to push you out of your comfort zone, and keep you there

▶ if you do the work. . .

▶ readings

▶ class activities

▶ exercises

▶ . . . you will succeed

⇒ *you don't have to be a genius*

Three aims

We will go through a series of models and learn

- ▶ when to use them
- ▶ how to use them + limitations
- ▶ how to understand the results

⇒ *The portfolio exam tests these learning outcomes. Class activities help you acquire them*

Aim 1: When to use a model

A mental map over data structures, different outcomes and what models to use

- ▶ Structure of class: topics decided by
 - ▶ the measurement level of the dependent variable (GLMs)
 - ▶ the data structure: nested data and missing data
- ▶ Group work
 - ▶ Presentation: theoretical “highlights” of topic
- ▶ Exam:
 - ▶ executive summary of the class

⇒ When you see data in the future, you know where you are and where to look for more info.

Aim 2: How to use a model

Intuitive understanding of the models: estimation (in R) and assumptions

- ▶ Structure of class:
 - ▶ day 1: lecture on theory
 - ▶ day 2-etc.: R seminar
- ▶ Group work
 - ▶ Portfolio presentation: results from replication + R-codes on Absalon
 - ▶ Presentation: theoretical “highlights” of family
- ▶ Exam:
 - ▶ 2 replication exercises + critical assessment
 - ▶ you can hand in a draft for feedback beforehand

⇒ *Once you know some of these models, you have the intuition for regressions in general.*

Aim 3: How to understand the results

Interpretation and communication of results

- ▶ Structure of class:
 - ▶ day 1: what goes into the model (recoding + propability distribution)
 - ▶ day 2: what comes out of the model (results)
- ▶ Seminar
 - ▶ My R-notes and your R-tips
 - ▶ text
 - ▶ numbers
 - ▶ visuals
- ▶ Exam:
 - ▶ take the model results seriously
 - ▶ go beyond the authors

⇒ *Communication == understanding, but also a superpower.*

Peer learning

Peer learning

This is a class designed for peer learning, because we learn much more

- ▶ **Group responsibility:** each group is responsible for a topic (Thu-Thu)
 - ▶ Presentation (theory)/R-codes (replication)
- ▶ **Group exam**
 - ▶ you can coauthor the portfolio (BA students with BA students; MA students with MA students)
- ▶ **Colloquiums**
 - ▶ meet up and exchange (codes, insights, feelings...)

A few hacks and other advice

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- ▶ **Use your calendar:**
 - ▶ your group week is going to be busy
 - ▶ assignments are discussed few days after they are shared
- ▶ **Group work prepares you for the exam**
 - ▶ theory presentation → mental map → executive summary
 - ▶ R-codes → how to → portfolio
- ▶ **Coauthor the exam**
- ▶ **Keep faith (in yourself)**
 - ▶ if you do the assignments, you pass the exam

Practicalities

Practicalities

- ▶ The final hand-in of the portfolio June 1st
- ▶ Group weeks/student activities:
 - ▶ put your name down on the spreadsheet on Absalon
 - ▶ you must choose 2 out of 3 activities (unless you do `shiny`, `rmarkdown` or ChatGPT)