### regression

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### <u>outline</u>

2016 elections bonus: wrong prediction

intuition of inference (inferential statistics)

multivariate: intuition

wages example

interpretation and practice

violations (Wheelan, ch12)

### quizz 1

- some looked at relationship between bridge the gap and enrollment
  - or some school lev success such as graduation or even salary of a graduate but it clearly said what y was
- oper dating some people proposed experiment: measure happiness and then assign to dating, but probably unethical!!

### ps4/ps5

- ♦ it always helps do define precisely your X, Y, U/A!!
- external validity: need to say if sample was random!
- internal validity: discuss some threats
- · really need experiment or at least a quasi experiment
- odon't say increased, large etc—use numbers, esp graphs, be specific!
- $\diamond$  INUS one more time—someone give a good example: first X->Y, and then how is X: I,N,U,S (spell out!) ?

### ps4/ps5

- omany people talk about experiments that are not!! need random assignment!! (and it needs to be ethical)
- · intervention or treatment without random assignment is fine, and can still do before after but it is not experiment!!
- ♦ again ask me and GA about data, but also go to the library and ask data librarian!!

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### wrong prediction! also see Wheelan (2013, ch10) concepts from this class help explain

- omany states were wrongly predicted!
- ♦ remember no prediction argues 100% certainty
- eg what people say in polls must be accompanied by actual action (voting)
- · majority voicing support for candidate in polls does not cause candidate to win
- · mere INUS condition, eg "shy Trump"
- and Trump voters may not want to talk to pollsters at all • not only candidate support matters; also propensity to vote!

### not only stats failed with election prediction

- way of running it failed too!
- Hilary was data driven
- · doing what models tell her to do
- Donald had a gut feeling
- · doing what intuition tells him what to do
- and often gut feeling wins!
- ·unknown unknowns, INUS condition, etc
- · extreme difficulty to argue anything without experiment
- odata and statistics usually help, but are not everything!

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### finding answers ogot hypotheis?

- onow it's time to analyze the data or critique research
- that's inference: drawing conclusions (making inferences)
   from data
   just use regression and "control" for other variables
- [elaborate later]

  this is what we want to know after all!
- We have research questions, turn them into hypotheses

·H1: Soc sci PhD graduates make more than non-PhD

- · (a brief clear testable statement)
- eg research Q: soc sci PhD good for career?
- oexciting to know it, right ?

### and why regression is better

- the regression advantage:
  look at many variables at the same time
- when just compare 2 means, the problem is that you are often comparing apples to oranges
- ·say you compare income for males and females
- $\cdot\,\mbox{but}$  you need to take into account that females have kids...
- · females are discriminated, etc
- regression will take care of that-keep that in mind

### examples

- see some of the useful things you can predict
- ♦ http://ianayres.yale.edu/prediction-tools eg life expectancy http://www.northwesternmutual.com/
  - learning-center/the-longevity-game.aspx

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#### multivariate OLS

- omultiple (multivariate) regression is the most common tool in social science
- t finds effect of a variable of interest (X) on the dependent variable (Y) controlling/holding constant other vars
- oit's a statistical trick that makes sample equal on all characteristics that we control for and imitates experimental setting (randomization)
- · again, in experiment you randomize into treatment and control groups so that both groups are on average the same and then we apply treatment (e.g. drug) to treatment group and see if had effect as compared to control group

multivariate ols: intuition

### multivariate OLS

- omost of the time cannot do experiment:
- · can't tell some people to smoke and some not can't give college to some and not others
- but can use regression!
- $\diamond$  eg: study effect of education (X) on income (Y)
- ·but it may not be the same for males and females?
- · just control for gender in regression
- and the effect is as if everybody had the same gender!

multivariate ols: intuition 15/42

### multivariate OLS

$$\diamond X \to Y$$
 can say that X affects Y

$$\diamond Y = f(X)$$
 or: Y is is a function of X (same thing)

$$\diamond Y = f(X_1, X_2, ..., X_n, u)$$

♦ in soc sci **always** many Xs

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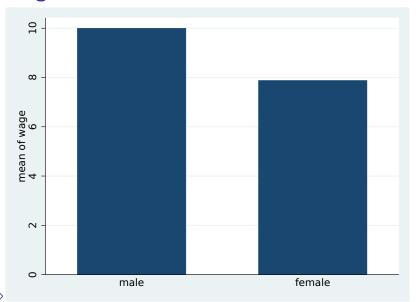
wages example

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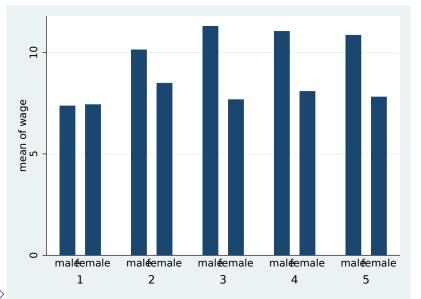
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### wages



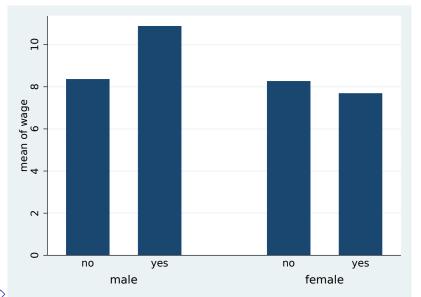
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### wages by quintile of experience



wages example 19/42

### wages by marital status and experience



wages example 20/42

### descriptive stats

Variable	0bs	Mea	ın Std.	Dev. M	Min Max
educ	534  534  534  534	9.0 13.0 17.8	)2 5. )1 2.	6	1 44.5 2 18 0 55
		O	educ	exp	
wage educ	1.	00			

exp | 0.08 -0.35 1.00

wages example 21/42

### interpreting coefficients opretty much only one way to interpret reg correctly

 $\diamond 1$  unit (\$ % etc) increase in X leads to  $\beta$  unit (\$ % etc) increase/decrease in Y (> 1X: remember ceteris paribus!)

increase/decrease in Y (> 1X: remember ceteris paribus
 and as per Wheelan ch11: focus on:

· ◇sign ◇size

 $\diamond$  significance:  $\cdot$  t-stat, t=coeff/se, sig if |t|>2

• p is prob of getting this result or larger if no assoc (Wheelan p198), sig if p < .05• 95% CI = +2 \* se

### multivariate ols

oext cre: why married insignificant?

wage		Std. Err.	t	P> t
educ	.9188352	.081526	11.27	0.000
exp	.0986602	.0178812	5.52	0.000
married	.5704847	.4357421	1.31	0.191
_cons	-5.07037	1.224631	-4.14	0.000

wages example 23/42

### now let's turn to cars!

- ♦ let's say we want to explain price with mpg and weight
- ◇research Q: fuel efficient cars don't have to cost a fortune
- ♦ hypothesis: the higher the mpg, the lower the price
- ♦ but the problem with fuel efficient cars is that they are tiny
- ♦ but the problem with fuel efficient cars is that they are tiny
   and cannot really use them for much

vages example 24/

### interpret: $\beta$ , p, t, CI; predict price for 10mpg

```
price | Coef. Std. Err. t P>|t| [95% Conf. Interval]
______
  mpg | -238.8 53 -4.50 0.000 -344, -133
_cons | 11253 1170 9.61 0.000 8919, 13587
price | Coef. Std. Err. t P>|t| [95% Conf. Interval]
  mpg | -49.5186 .15 -0.57 0.567 -221, 122
weight | 1.746 .64 2.72 0.008 .46, 3
_cons | 1946 3597 0.54 0.590 -5226, 9118
```

wages example 25/42

## $\diamond$ weight=-118+4.3\*(height in)+.12\*(age)-4.8\*(female) $\diamond$ 53yo female who is 5'5:

- $\diamond$ -118+(4.3\*65)+(.12\*53)-(4.8\*1)=163
- ♦35yo male who is 6'3:

predicted values (p200 Wheelan, 2013)

- •https://www.northwesternmutual.com/learning-center/
- tools/the-longevity-game

  banks, insurance companies, etc
- . use models like this to predict whether you'll repay loan
- · use models like this to predict whether you'll repay loan · and hence how risky you are, and whether you should get

### a "complete" explanation

owage=f(native ability, education, family background, age, gender, race, height, weight, strength, attitudes, neighborhood influences, family connections, interactions of the above, chance encounters,...)

 multiple regression will tell you the effect of one variable while controlling for the effect of other variables (again, as if everybody was the same on other vars)

 $\diamond$  wage<sub>i</sub> =  $\beta_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + ... + \beta_n X_{ni} + u_i$ 

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### practice regressions interpretations

♦ Happy Tourists, Unhappy Locals http:

//link.springer.com/article/10.1007/s11205-016-1436-9

### ps6: flip the class!

- was it difficult?
- any challenges?
- oneed to cover anything about regression again?

interpretation and practice 30/42

### do scatterplots

- ⋄it is useful to produce a scatterplot
- you'd see outliers and whether the relationship is due to them
- · blackboard: relationships biased due to outliers
- ·say marriage rate and divorce rate across states

### think about it

- always interpret results!
- give it some thought
- ♦ ask yourself whether results make sense and why
- ♦ think about measurement and what it means
   eg does marriage cause divorce or sth about NV?
- and as always, remember design principles:
- INUS condition
- threats to validity
- ♦ and note that in addition to regression
- ·it is critical to have theory/logic/mechanism
- ·see Wheelan (2013, p207)

### Wheelan in ch11 mentions Whitehall studies

- ♦ fascinating stuff!
- high status causes better health!
- great book 'Status Syndrome' http://a.co/jaUuwT7
- ⋄say nobel prize or oscar boosts one's health and longevity
- · these successful folks live longer and in better health
- · than exact same people (income, lifestyle, etc) but without status

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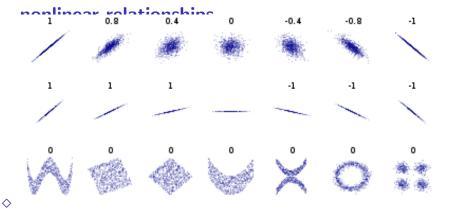
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# do not kill people with regressions (p212 Wheelan, 2013)

- recently tens of thousands of females
   were killed or made sick with estrogen,
   because regressions showed that estrogen was good
- regression estimates are never causal by themselves!
- oremember the gold standard: experiment!
- ·again, INUS, unknown unknowns, corr≠causation, etc

violations (Wheelan, ch12) 35/42



- ♦ like corr, won't detect nonlinear relationships!
- · example of nonlinear rel? extra credit!
- · [need quadratics, logs, etc] BUT!:
- ♦ just break it up into subsets/subsamples! dig deeper!
- ·say for males and females separately

### reverse causality (p216 Wheelan, 2013)

- $\diamond$  more lessons—->bad golf, or
- ♦ bad golf—
  >more lessons
- ⋄ solution:
- · lag variable: bad golf last month—— >more lessons now
- · use exogenous shock–remember from res\_des.pdf:
- ·terrorist attack—— >policing—— >crime
- or think about it! miserable people choose cities?
- $\cdot$ then i looked at only people who were born in urban/rural

violations (Wheelan, ch12)

### omitted variable bias (p217 Wheelan, 2013)

- ♦golf— >heart disease and cancer?
- ·control for age!
- ·age is killing people, not golf!

violations (Wheelan, ch12) 38/4

### extrapolate beyond data (p220 Wheelan, 2013)

- ⋄only interpret within range of data!
- draw say regression of fear on age
- · and reg line hits y-axis at -3

violations (Wheelan, ch12) 39/42

### data mining (p221 Wheelan, 2013)

- ♦ if you torture your data enough, it will confess
- likewise, if you throw enough variables, you will
- find significant relationships
- but remember: you need theory, causal mechanism/path, story!

violations (Wheelan, ch12) 40/4

### run it excel ·http: //www.westmont.edu/~phunter/ma5/excel/regression.html http://www3.wabash.edu/econometrics/ EconometricsBook/Basic%20Tools/ExcelAddIns/ OLSRegression.htm http://finance.wharton.upenn.edu/~bodnarg/courses/ readings/regression python http://www.learndatasci.com/

predicting-housing-prices-linear-regression-using-python https://stackoverflow.com/questions/19991445/

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run-an-ols-regression-with-pandas-data-frame

violations (Wheelan, ch12)

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