# Quantitative Methods

## Human Sciences, 2020–21

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Lecture 8: 3 December 2020

# Today

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- A third theory of inference.

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- Three forms of systematic bias.

# Neyman-Pearson hypothesis testing

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- Note: all tests are done "under" (i.e., assuming) $H_0$.

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- *p*-value: the probability of obtaining something at least as extreme as the observed *z*-statistic, assuming $H_0$ is true.
- Common mistake: the *p*-value is *not* the probability that $H_1$ is false. (Why not?)

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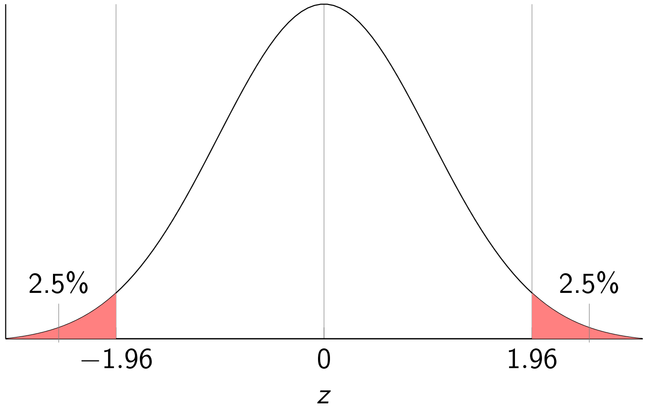

# Neyman-Pearson hypothesis testing: example

```
##
## Call:
## lm(formula = y ~ x, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -14.8208  -3.1487   0.0409   3.1336  13.1631
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.23379    0.50486   0.463    0.644
## x            5.11564    0.08244  62.052   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.755 on 498 degrees of freedom
## Multiple R-squared:  0.8855,Adjusted R-squared:  0.8852
## F-statistic:  3851 on 1 and 498 DF,  p-value: < 2.2e-16
```

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- Implication: the common causes of any pair of variables in the graph must also be in the graph.

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- The causal graph depicts this knowledge for an experiment in which cigarettes are randomly assigned to a treatment group.

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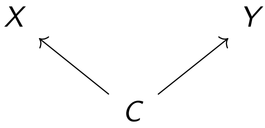


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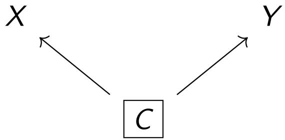


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- $C$ is a *confounder* of the association between $X$ and $Y$.
- If we do condition on $C$, we block the association between $X$ and $Y$ (via conditional independence).

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- This is known as *selection bias* (via conditional dependence).

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- In general, the path $X \leftarrow C \rightarrow Y$ cannot be blocked by conditioning on mismeasured confounder $C^*$.

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4. Random variability (disappears as $n \to \infty$).

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  1. Confounding: not conditioning on common causes.
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  3. Measurement: information error.
- These biases may arise in observational studies *and* in randomised experiments (how?).