



# Empirical tests of directional dependence

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# Directional dependence

Dodge & Rousson (2000, 2001)

Attempt at devising a statistical tests that yields a decision whether variable  $X$  caused variable  $Y$ , or vice versa



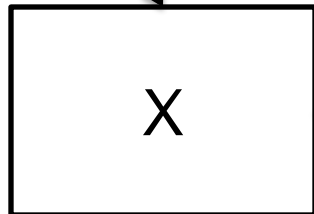
# Directional dependence

- Introduction to social scientists and case studies
  - Von Eye, & DeShon (2011, 2012)
- Simulation studies
  - Pornprasertmanit, & Little (2012)

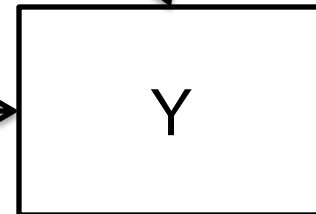


# Directional dependence

$$\varepsilon_X \sim N(\mu, \sigma)$$



$$\varepsilon_Y \sim N(0, \sigma)$$



$$Y = \beta_0 + \beta_1 X + \varepsilon$$



# Directional dependence

- Is expected to work:
  - When cause is non-normally distributed
  - When relationship to effect is linear
  - When effect is function of non-normally distributed cause and normally distributed random disturbances



# Directional dependence

- Is expected *not* to work:
  - When cause is normally distributed
  - When relationship to effect is non-linear
  - When effect is function of other (non-normally) distributed variables, in addition to the putative cause



# Tests of directional dependence

- Differences in skew:
  - If variable  $X$  has more skew than  $Y$ , then conclude that  $X$  causes  $Y$
- Differences in kurtosis:
  - If variable  $X$  has more (excess) kurtosis than  $Y$ , then conclude that  $X$  causes  $Y$
- Differences in D'Agostino's  $K^2$ 
  - If variable  $X$  has larger  $K^2$  than  $Y$ , then conclude that  $X$  causes  $Y$



# Tests of directional dependence

- Tests rely on statistical significance tests (often bootstrapped) of correlations, skew, kurtosis,  $K^2$ , and differences in skew, kurtosis, and  $K^2$





# Outcome of tests

## Neither

- No significant correlation
- Some special conditions in which sign of correlation coefficient and sign of difference in skew, or kurtosis are in contradictory directions



# Outcome of tests

## Undetermined

- Significant correlation, but *neither* variable exhibits significant skew, kurtosis, or  $K^2$ , or difference in skew, kurtosis, or  $K^2$  is not significant



# Outcome of tests

$$X \rightarrow Y$$

- Significant correlation, variables have significant skew, kurtosis, or  $K^2$  and skew, kurtosis, or  $K^2$  is significantly larger in X than in Y



# Outcome of tests

$$Y \rightarrow X$$

- Significant correlation, variables have significant skew, kurtosis, or  $K^2$  and skew, kurtosis, or  $K^2$  is significantly larger in Y than in X



# My own biases

**“No causes in, no causes out.”**

Nancy Cartwright, “Hunting Causes and Using Them”



# My own biases

- I was fundamentally opposed to the general concept of inferring causal direction from a statistical test
- I was unconvinced by published case studies
- I accepted simulation results but heavily questioned whether real data would conform to the conditions of the simulation study that resulted in good performance
- I conducted my study with the hope of showing the bad performance of directional dependence test



# Test database

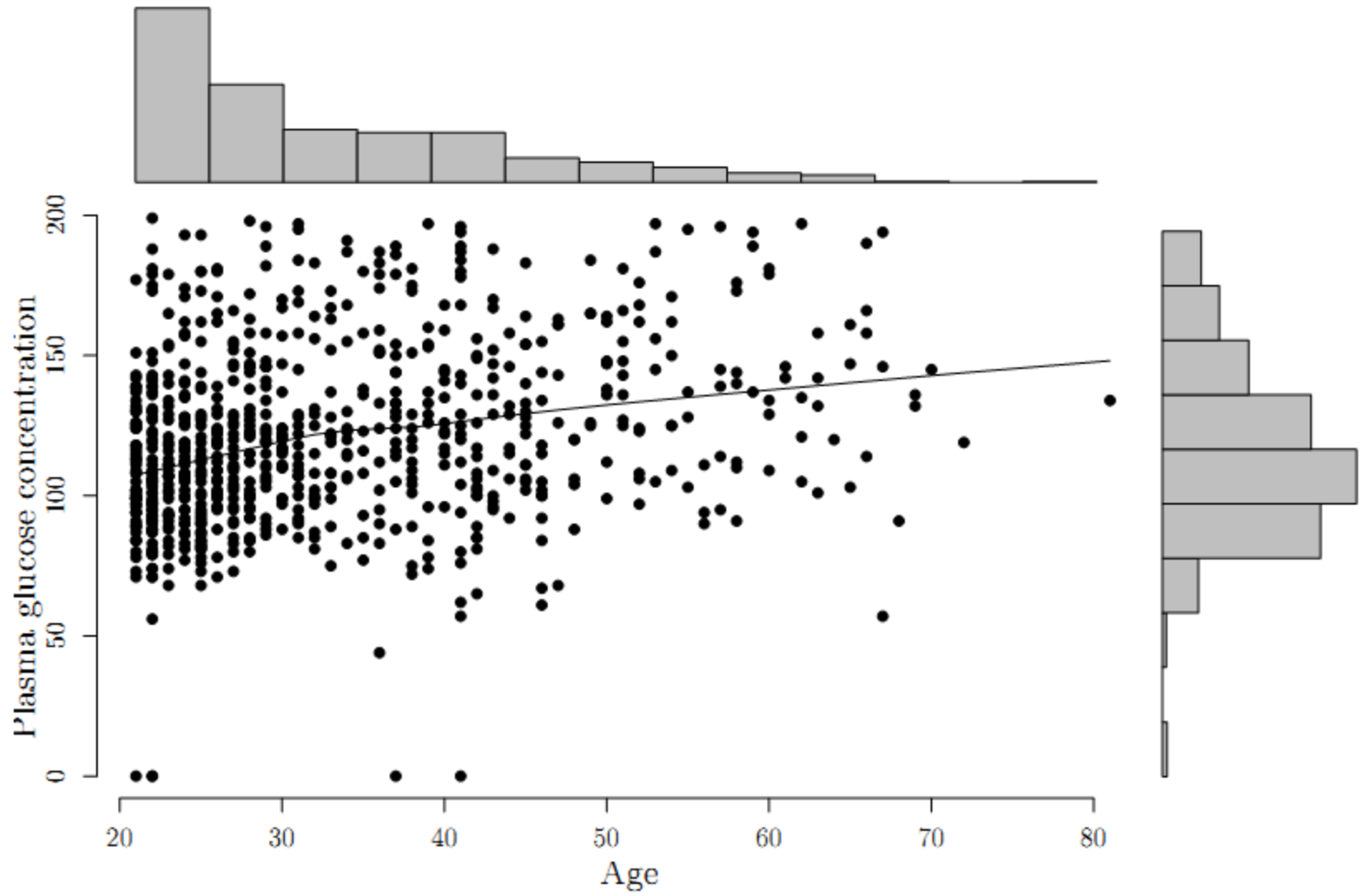
- Max-Planck Institute for Biological Cybernetics database on cause-effect pairs
- Total of 65 independent, two-variable pairs with continuous variables
- All were tested with all three directional dependence tests

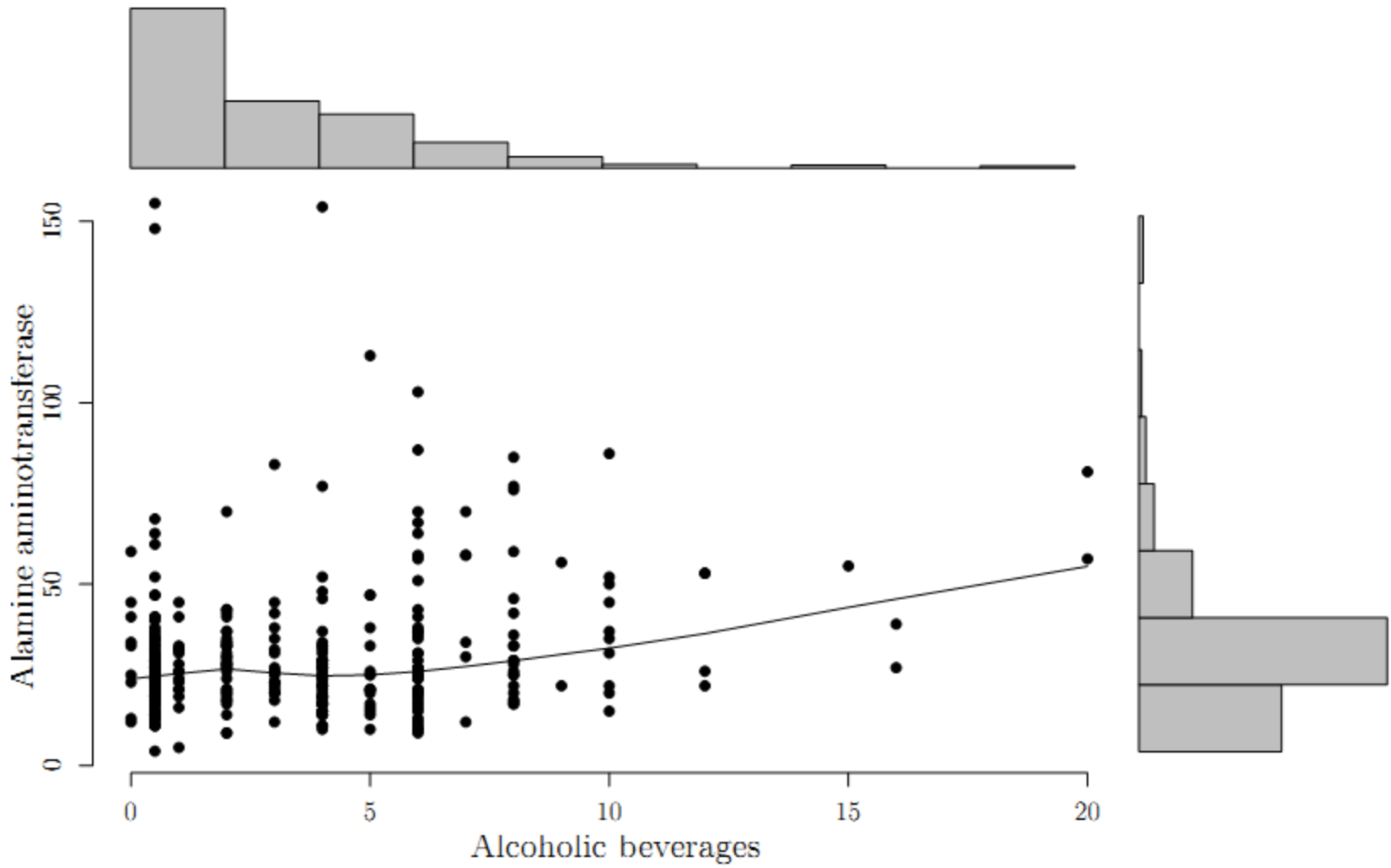


# Test database

- “Benign” subset was selected that consisted of variables that
  - Had at least one variable that was significantly non-normal
  - Had linear relationships
  - Had no outliers (Cook’s D)
  - Had normally distributed residuals in the true model









# Performance of the tests

|                | All pairs |      |          |
|----------------|-----------|------|----------|
|                | $K^2$     | Skew | Kurtosis |
| Correct        |           |      |          |
| Incorrect      |           |      |          |
| Wrong variable |           |      |          |
| Undetermined   |           |      |          |
| Neither        |           |      |          |



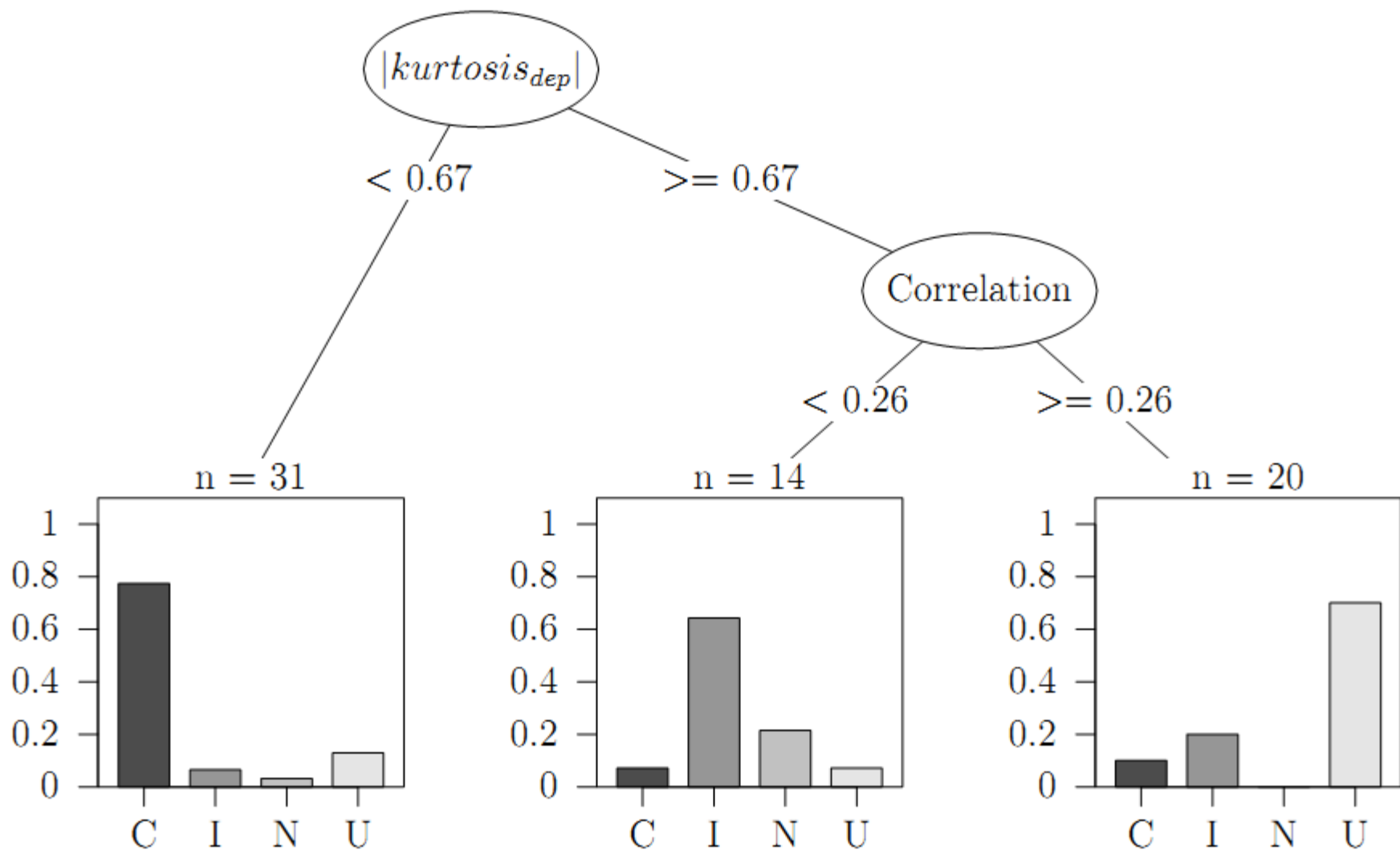
# Features that make the tests work

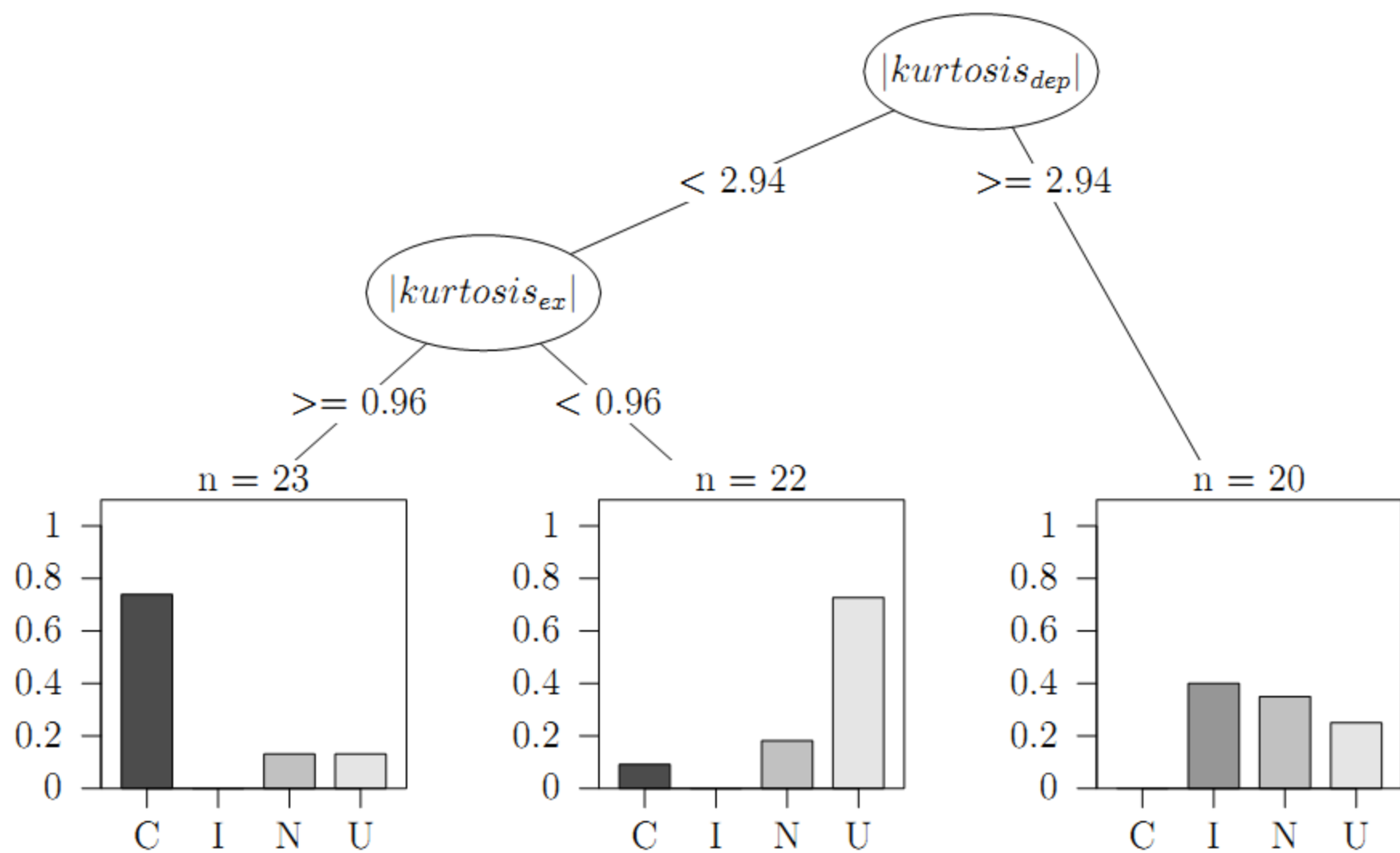
- We used both logistic regression, and regression trees to examine whether particular features of the data make it more or less likely that a directional dependence test yields a correct results

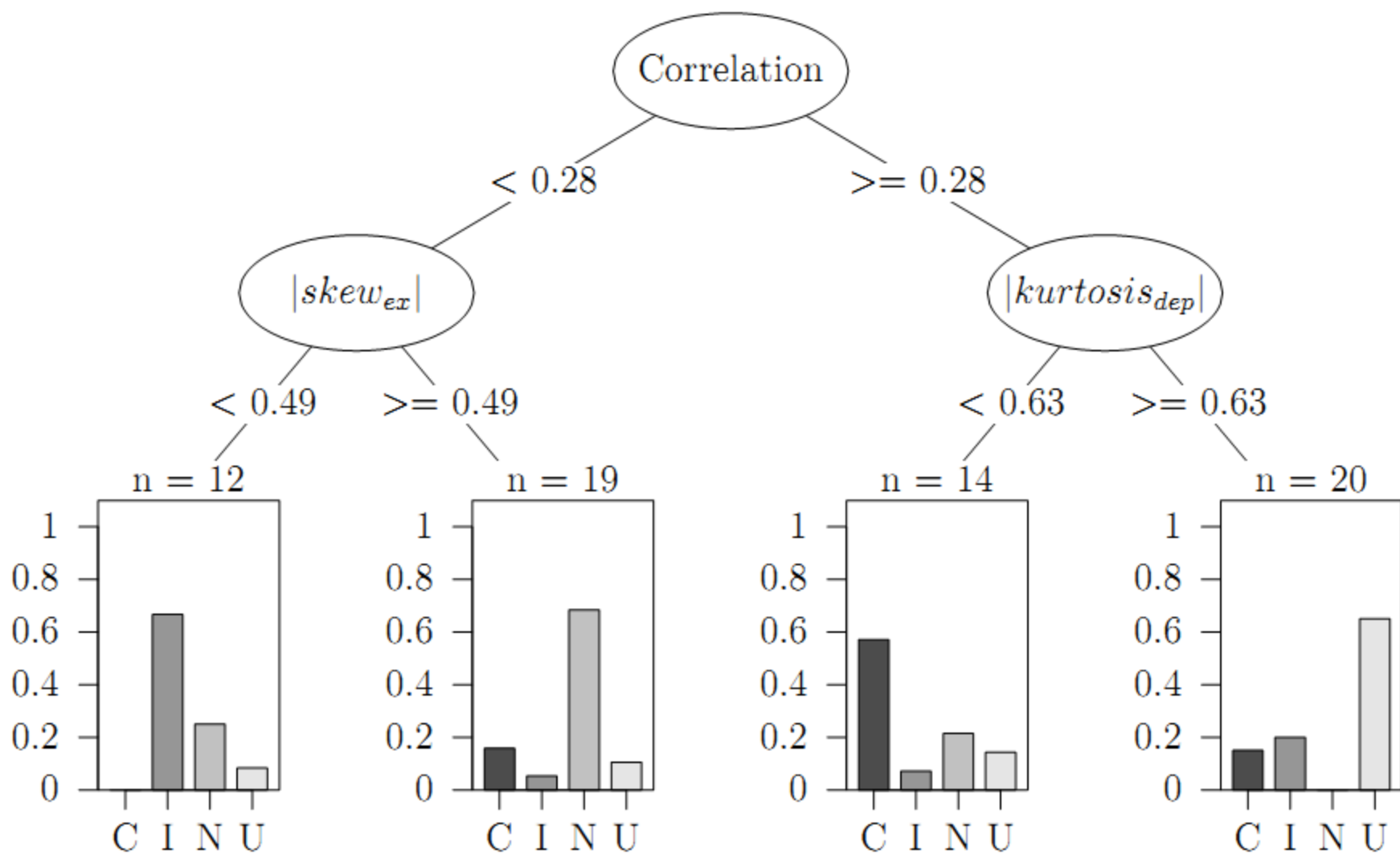


# Features that make the tests work

- Results somewhat expected (e.g., if kurtosis of cause is very large, tests based on kurtosis perform well)
- Results also not very informative, because they yield no insight into what an applied researcher could use as a warning sign that the test is not likely to perform well











# Discussion



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