Business Analytics
Data Preparation and Causal Inference

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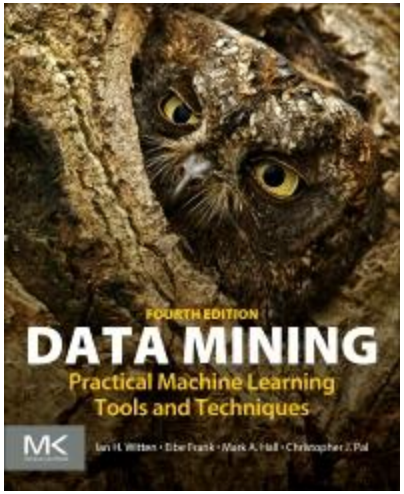
Course Content

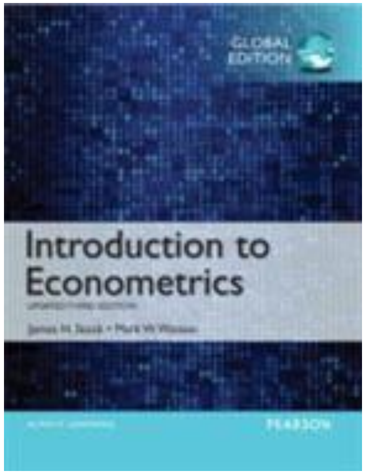
- Introduction
- Regression Analysis
- Regression Diagnostics
- Logistic and Poisson Regression
- Naive Bayes and Bayesian Networks
- Decision Tree Classifiers
- **Data Preparation and Causal Inference**
- Model Selection and Learning Theory
- Ensemble Methods and Clustering
- High-Dimensional Problems
- Association Rules and Recommenders
- Neural Networks

Recommended Literature

- **Data Mining: Practical Machine Learning Tools and Techniques**
  - Ian H. Witten,Eibe Frank,Mark A. Hall, Ch. Pal
  - http://www.cs.waikato.ac.nz/ml/weka/book.html
  - Section: 6.1, 8.1, 8.2



- **Introduction to Econometrics**
  - Stock, James H., and Mark W. Watson
  - Chapter 9, 10, 13



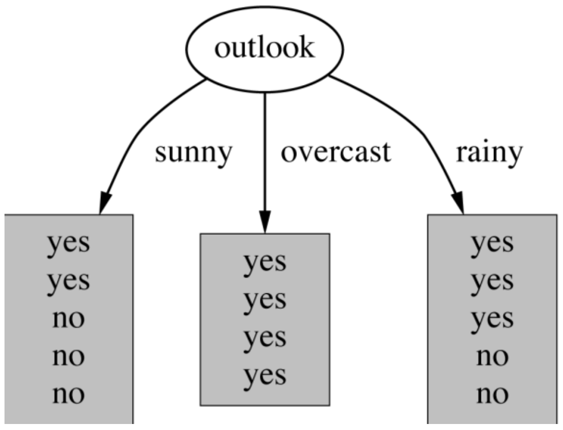
- Online material on causal inference in econometrics
  - Empirical Economics by Esther Duflo, MIT Economics
  - http://web.mit.edu/14.771/www/emp_handout.pdf

Outline for Today

- **Pruning of decision trees**
- CRISP-DM process model
- Data preparation
  - Data cleaning
  - Balanced training data
  - Discretization
  - Feature selection
- Causal inference

Decision Tree Algorithms

- At each node, available attributes are evaluated on the basis of separating the classes of the training examples
- A goodness function is used for this purpose
- Typical goodness functions:
  - information gain (ID3/C4.5)
  - information gain ratio
  - gini index (CART)



Computing Information (last Class)

- Information is measured in *bits*
  - Given a probability distribution, the info required to predict an event, i.e. if play is yes or no, is the distribution's *entropy*
  - *Entropy* gives the information required in bits (this can involve fractions of bits!)
- Formula for computing the entropy:

$$\text{entropy}(p_1, p_2, \ldots, p_n) = -p_1 \log p_1 - p_2 \log p_2 \ldots - p_n \log p_n$$

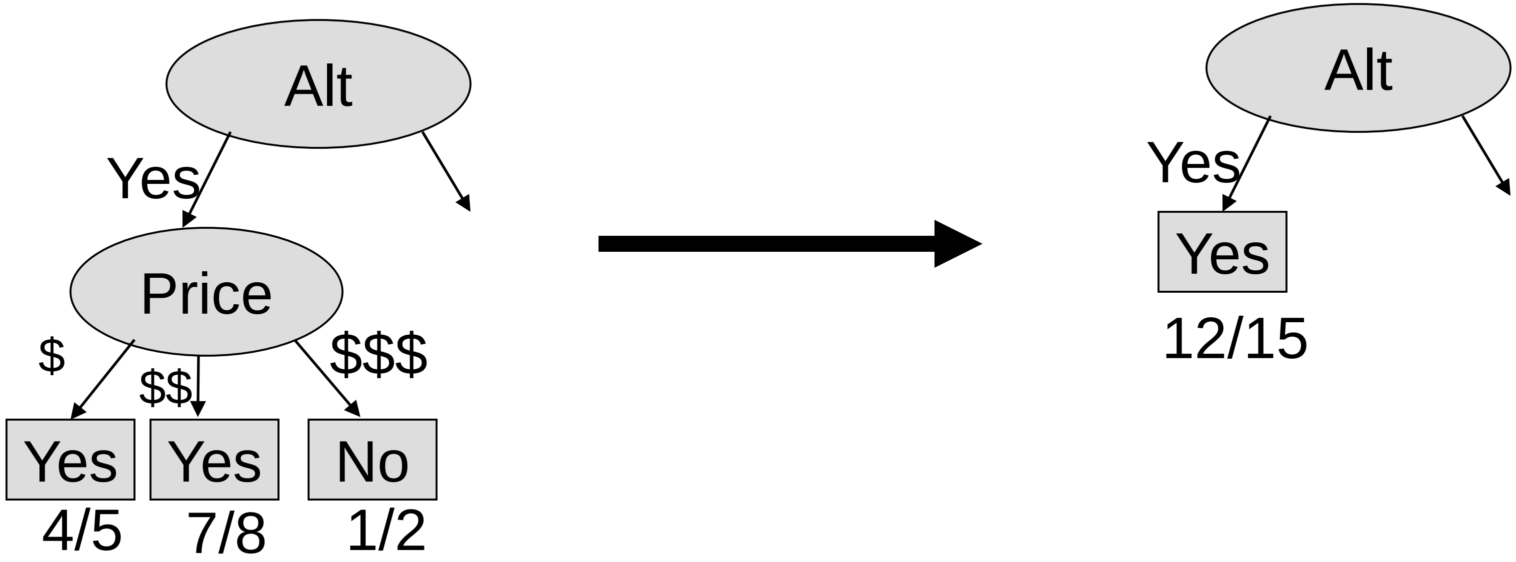
Pruning

- *Prepruning* tries to decide *a priori* when to stop creating subtrees
  - Halt construction of decision tree early
  - Use same measure as in determining attributes, e.g., halt if $\mathrm{gain}(S, a)$ < threshold
  - Most frequent class becomes the leaf node
  - This turns out to be fairly difficult to do well in practice

- *Postpruning* simplifies an existing decision tree
  - Construct complete decision tree
  - Then prune it back
  - Used in C4.5, CART
  - Needs more runtime than *prepruning*

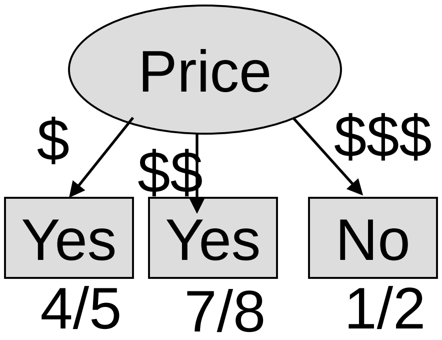
Postpruning

Subtree replacement replaces a subtree with a single leaf node (main method)



When to Prune a Tree?

- To determine if a node should be replaced, compare the error rate estimate for the node with the combined error rates of the children
- Replace the node if its error rate is less than combined rates of its children



err(3/15, 15) = 0.28

5/15 err(1/5,5) + 8/15 err(1/8, 8) + 2/15 err(1/2,2) = 0.33

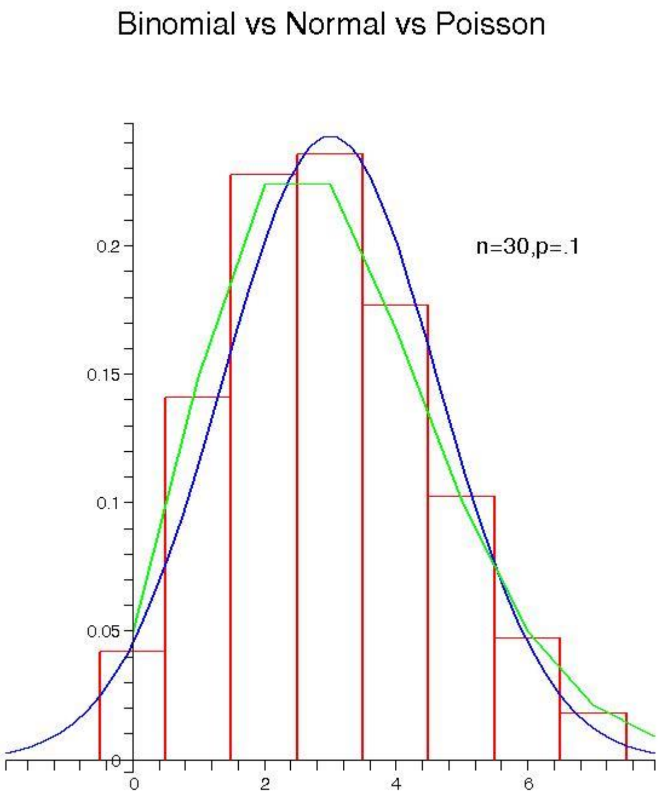
When to Prune a Tree?

- Prune only if it reduces the estimated error
  - Error on the training data is NOT a useful estimator
- Use a hold-out set for pruning (“reduced-error pruning”)
  - Limits data you can use for training

- C4.5’s method
  - Derive confidence interval from training data
  - Use a heuristic limit for the error rate, derived from the confidence interval for pruning
  - Shaky statistical assumptions (because it is based on training data), but works well in practice

Approximation of the Binomial Distribution

- "Observed error rate" $f = \frac{e}{n}$ with
  e = error,
  n = number of trials
- This random variable can be modeled as a Bernoulli process
- For large enough n (e.g., np>10), f follows a Normal distribution
  – Central Limit Theorem



Binomial PDF and Normal approximation for n=30 and p=0.1.

Central Limit Theorem Revisited

- The *central limit theorem* states that the standardized average of any population of i.i.d. random variables X_i with mean μ_X and variance σ^2 is asymptotically $\sim N(0,1)$, or

- Asymptotic Normality implies that $P(Z \leq z) \rightarrow \Phi(z)$ as $n \rightarrow \infty, or\ P(Z \leq z) \approx \Phi(z)$

$$Z = \frac{\bar{X} - \mu_X}{\sigma / \sqrt{n}} \sim N(0,1)$$

Using the Confidence Interval of a Normal Distribution

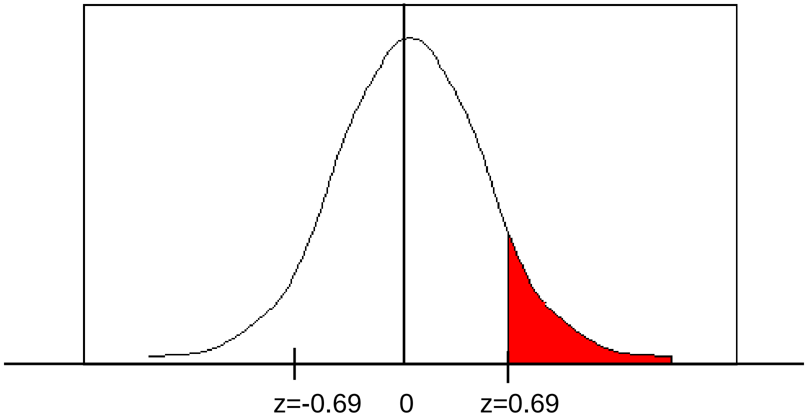
- C4.5 uses a heuristic limit for the error rate, derived from the confidence interval of the error rate for pruning
- x% confidence interval $[-z \leq X \leq z]$ for random variable with 0 mean is given by: $\Pr[-z \leq X \leq z] = x$

- With a symmetric distribution:

$$\Pr[-z \leq X \leq z] = 1 - 2\Pr[X \geq z]$$

Confidence Limits

- Confidence limits c for the standard normal distribution with 0 mean and a variance of 1:



$c = \Pr[X \geq z]$	z
0.1%	3.09
0.5%	2.58
1%	2.33
5%	1.65
10%	1.28
20%	0.84
25%	0.68
40%	0.25

- There is a 25% probability of X being > 0.68

$$\Pr[-0.68 \leq X \leq 0.68]$$

- To use this we have to reduce our random variable f to have 0 mean and unit variance

Transforming f

- Standardized value for observed error rate f :

$$\frac{\overline{X}-\mu}{\sigma/\sqrt{n}} = \frac{f-p}{\sqrt{p(1-p)/n}}$$

  (Standardization: subtract mean and divide by the standard deviation)

- Binomial conf. interval: $$\Pr\left[\frac{f-p}{\sqrt{p(1-p)/n}} > z\right] = c$$

- Solving for p provides limits for the confidence factor c:

$$p = \left(f + \frac{z^2}{2n} \pm z * \sqrt{\frac{f}{n} - \frac{f^2}{n} + \frac{z^2}{4n^2}}\right) \Bigg/ \left(1 + \frac{z^2}{n}\right)$$

- You prune the tree stronger
  - If c goes down => z goes up and also p goes up
  - If n goes down => p goes up
  - with p as an estimator for the error rate

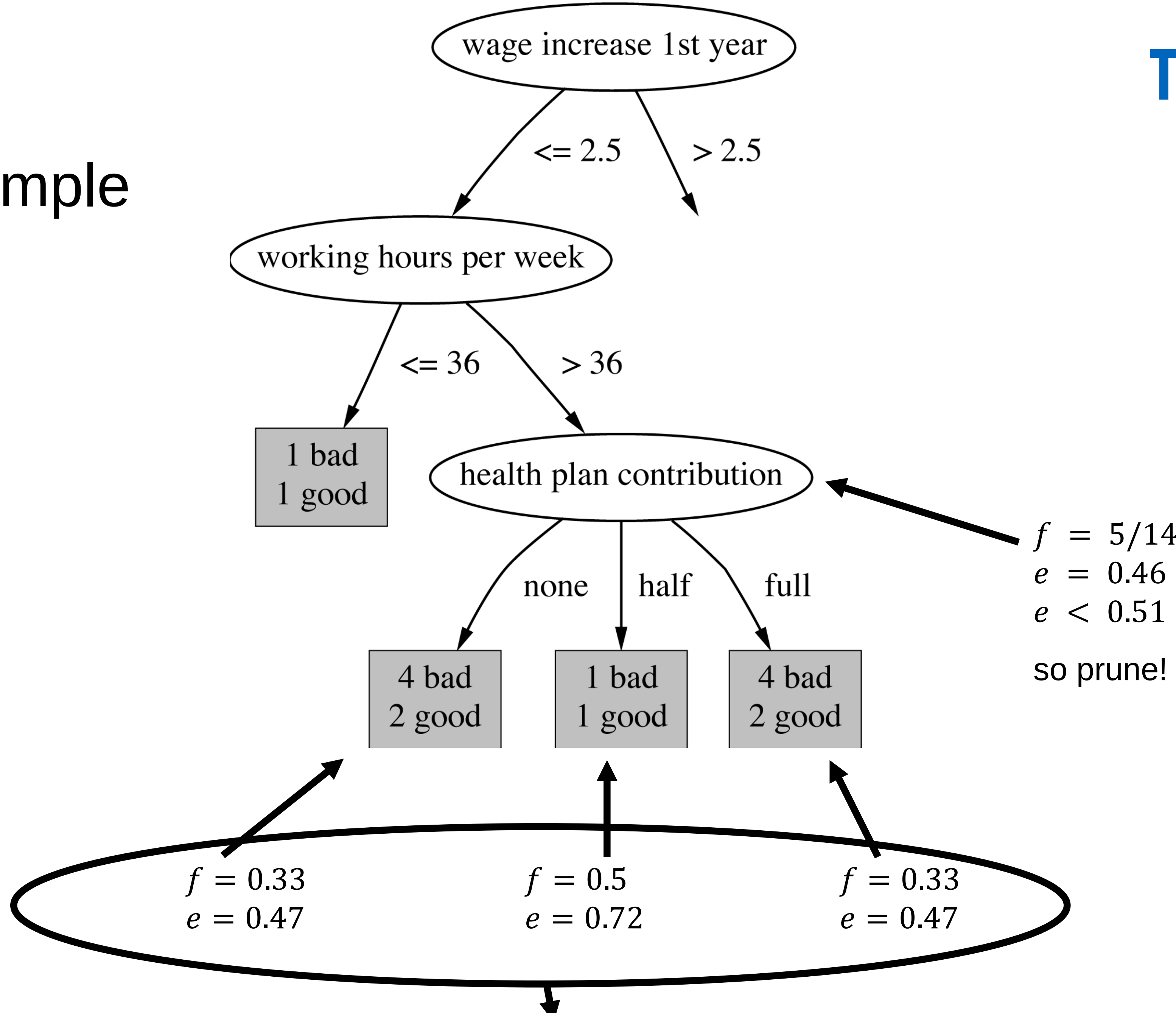
C4.5's Method

- Error estimate e for a node (:= upper bound of confidence interval):

$$e = p = \left(f + \frac{z^2}{2n} + z * \sqrt{\frac{f}{n} - \frac{f^2}{n} + \frac{z^2}{4n^2}} \right) \Big/ \left(1 + \frac{z^2}{n} \right)$$

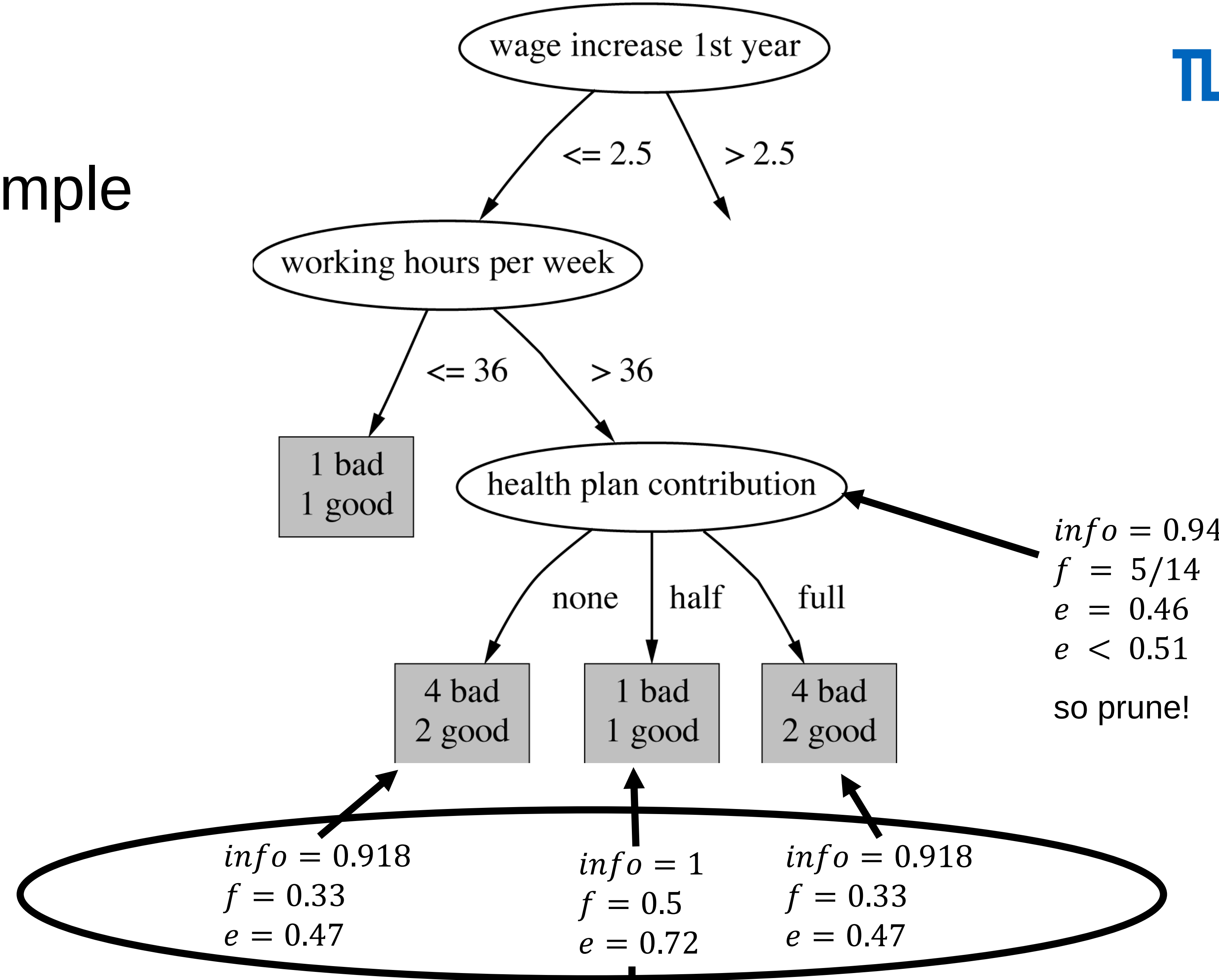
  – If confidence limit $c = 25\%$ then $z = 0.69$ (from Normal distribution)
  – f is the error on the training data
  – n is the number of instances covered by the node
- Even with pos. information gain, e might increase as well
- Error estimate for subtree is weighted sum of error estimates for all its leaves

Example



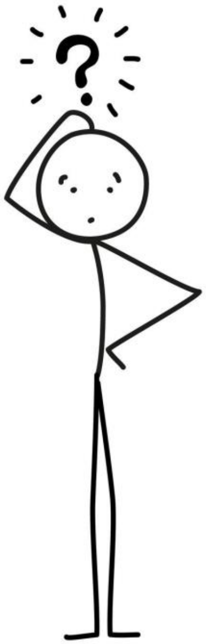
Combined and weighted using ratios 6:2:6 gives 0.51

Example



Info for sub-nodes = 0.92997, Combined and weighted using ratios 6:2:6 gives 0.51

Do you remember the pseudo code for decision tree learners discussed in the last class?



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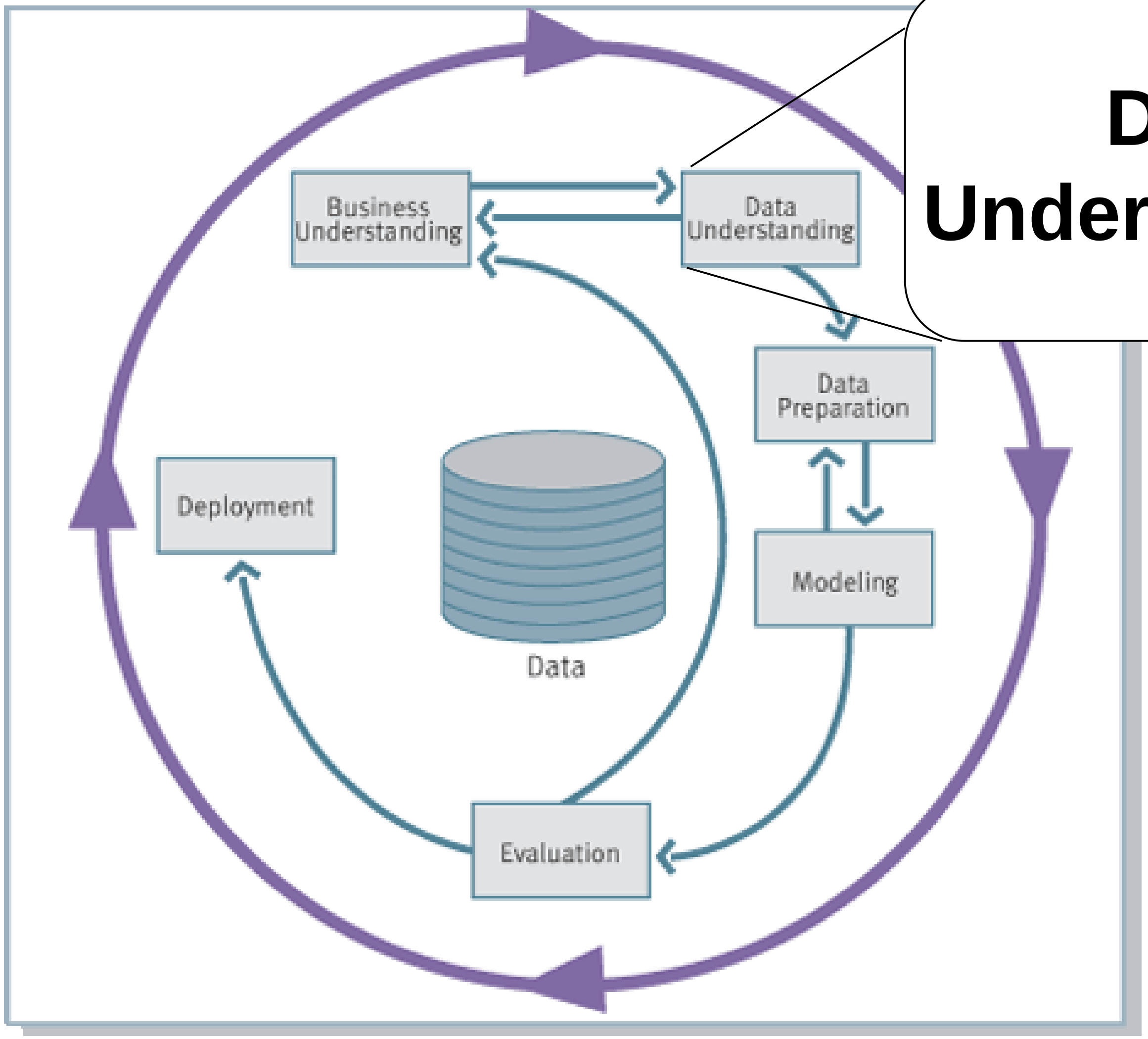
Knowledge Discovery Process



Data Understanding

Data Understanding: Quantity

- Number of instances (records)
  - Rule of thumb: 5,000 or more desired (nice to have)
  - if less, results are less reliable, use special methods (boosting, …)

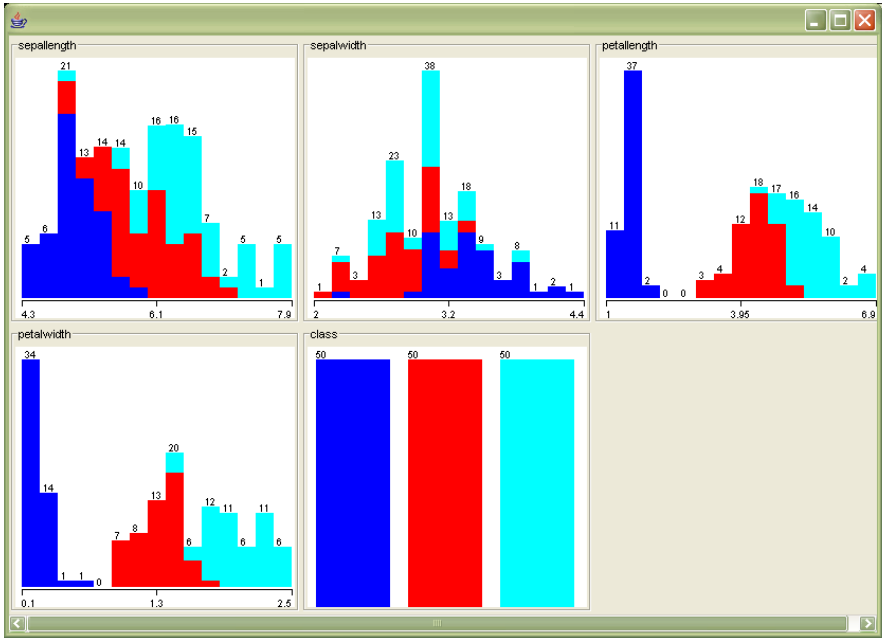
- Number of attributes
  - Rule of thumb: Start out with less than 50 attributes
  - If many attributes, use attribute selection

- Number of targets
  - Rule of thumb: >100 for each class
  - if very unbalanced, use stratified sampling

Data Understanding

- Visualization
- Data summaries
  - Attribute means
  - Attribute variation
  - Attribute relationships

- see R tutorial



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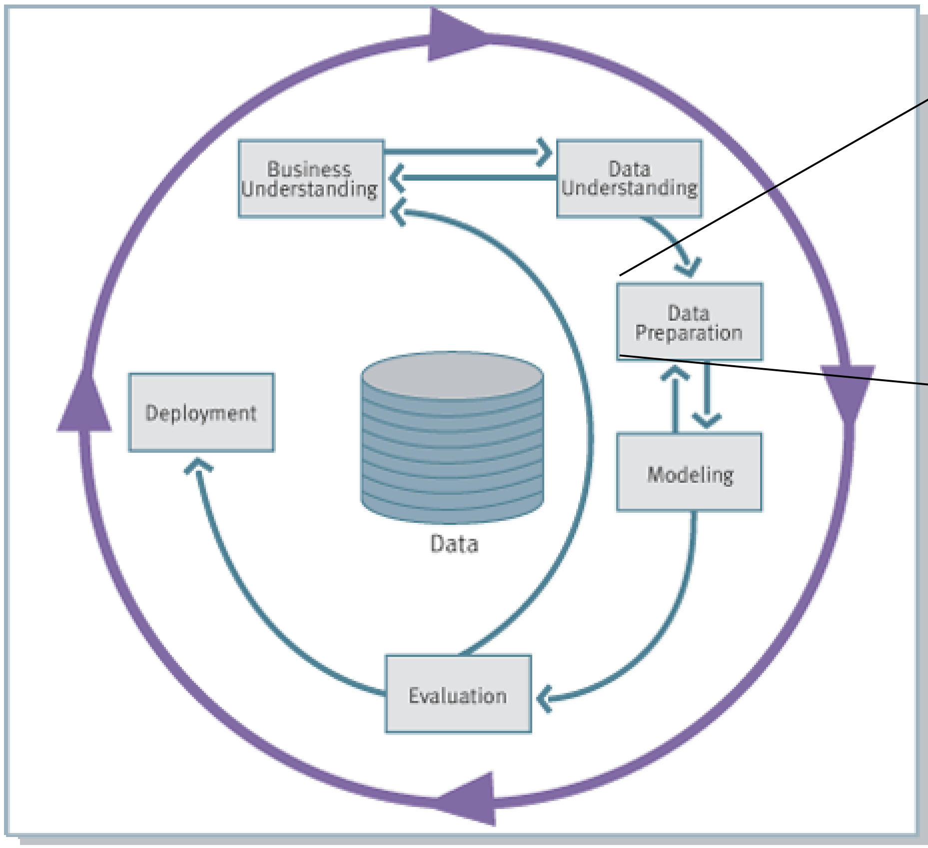


Data Preparation
(Witten, Frank: Chapter 8)

Data Preparation estimated to take 70-80% of the time and effort

Data Cleaning: Missing Values

- Missing data can appear in several forms:
  - <empty field> "0"   "." "999" "NA" …
- Standardize missing value code(s)
- Dealing with missing values:
  - Ignore records with missing values
  - Treat missing value as a separate value
  - Imputation: fill in with mean or median values

Conversion: Ordered to Numeric

- Ordered attributes (e.g. Grade) can be converted to numbers preserving *natural* order, e.g.
  - A → 4.0
  - A- → 3.7
  - B+ → 3.3
  - B → 3.0
- Why is it important to preserve *natural* order?
  - To allow meaningful comparisons, e.g. Grade > 3.5

Conversion: Nominal, Few Values

Multi-valued, unordered attributes with small no. of values

- e.g. $Color = Red, Orange, Yellow, \ldots$
- for each value v create a binary “flag” variable C_v , which is 1 if $Color = v$, 0 otherwise

ID	Color	…
371	red	
433	yellow	

ID	C_red	C_orange	C_yellow	…
371	1	0	0	
433	0	0	1	

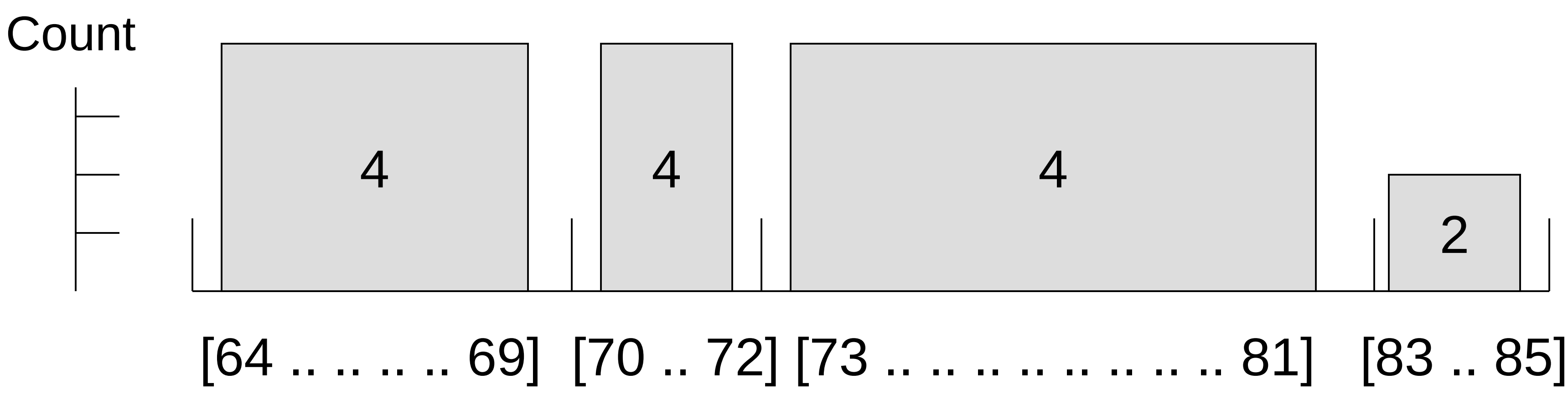
Nominal, many values: Ignore ID-like fields whose values are unique for each record

Data Cleaning: Discretization

- Discretization reduces the number of values for a continuous attribute
- Why?
  - Some methods can only use nominal data
    - e.g., in ID3, Apriori, most versions of Naïve Bayes, CHAID
  - Helpful if data needs to be sorted frequently
    - e.g., when constructing a decision tree
  - Some methods that handle numerical attributes assume normal distribution which is not always appropriate
- Discretization is useful for generating a summary of data
- Also called “binning”

Discretization: Equal-Frequency

Temperature values:
64 65 68 69 70 71 72 72 75 75 80 81 83 85



Equal Height = 4, except for the last bin

Discretization: Class Dependent (Supervised Discretization)

For example, based on information gain of the class variable (see C4.5)

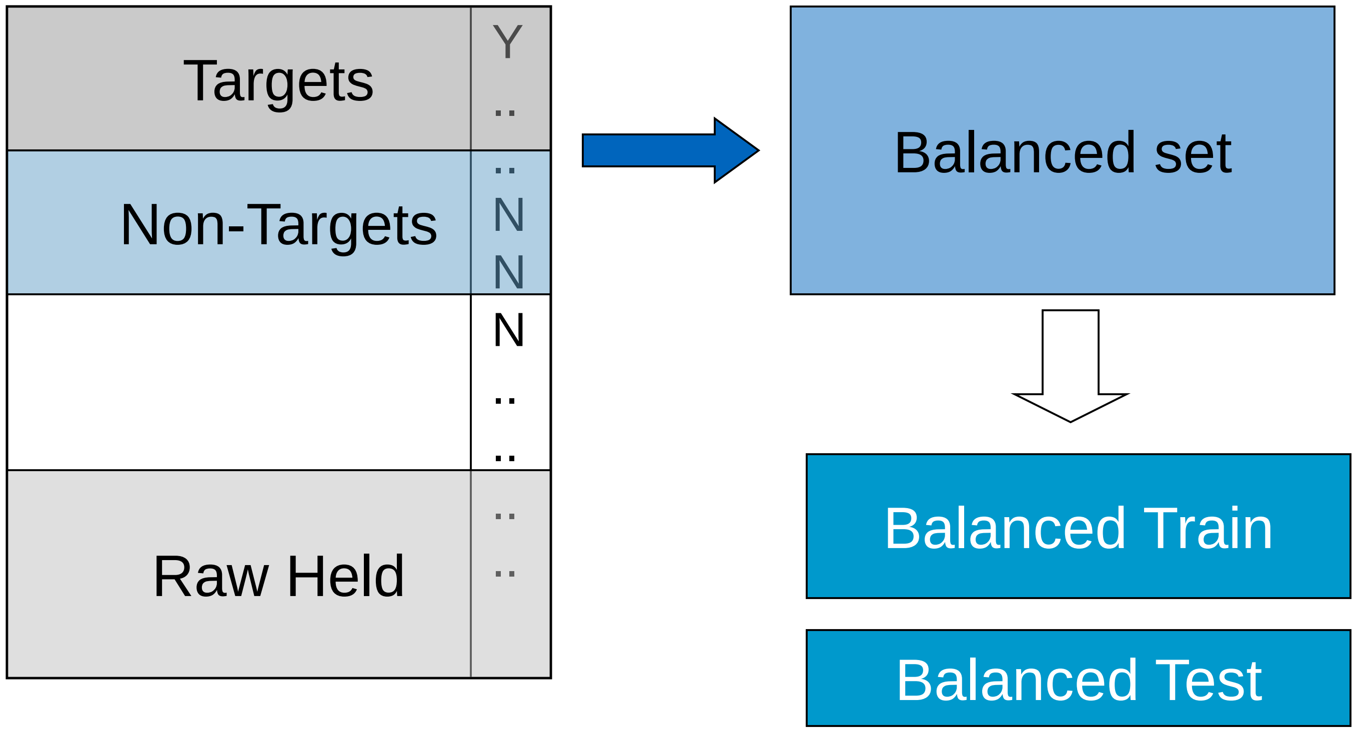
64	65	68	69	70	71	72	72	75	75	80	81	83	85
Yes	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	Yes	Yes	No

- Treating numerical attributes as nominal discards the potentially valuable ordering information
- Alternative: Transform the k nominal values to $k-1$ binary attributes
- The $(i-1)^{th}$ binary attribute indicates whether the discretized attribute is less than i

Unbalanced Target Distribution

- Sometimes, classes have very unequal frequency
  - Churn prediction: 97% stay, 3% churn (in a month)
  - Medical diagnosis: 90% healthy, 10% disease
  - eCommerce: 99% don’t buy, 1% buy
  - Security: >99.99% of Germans are not terrorists
- Similar situation with multiple classes
- Majority class classifier can be 97% correct, but useless

Building Balanced Train Sets

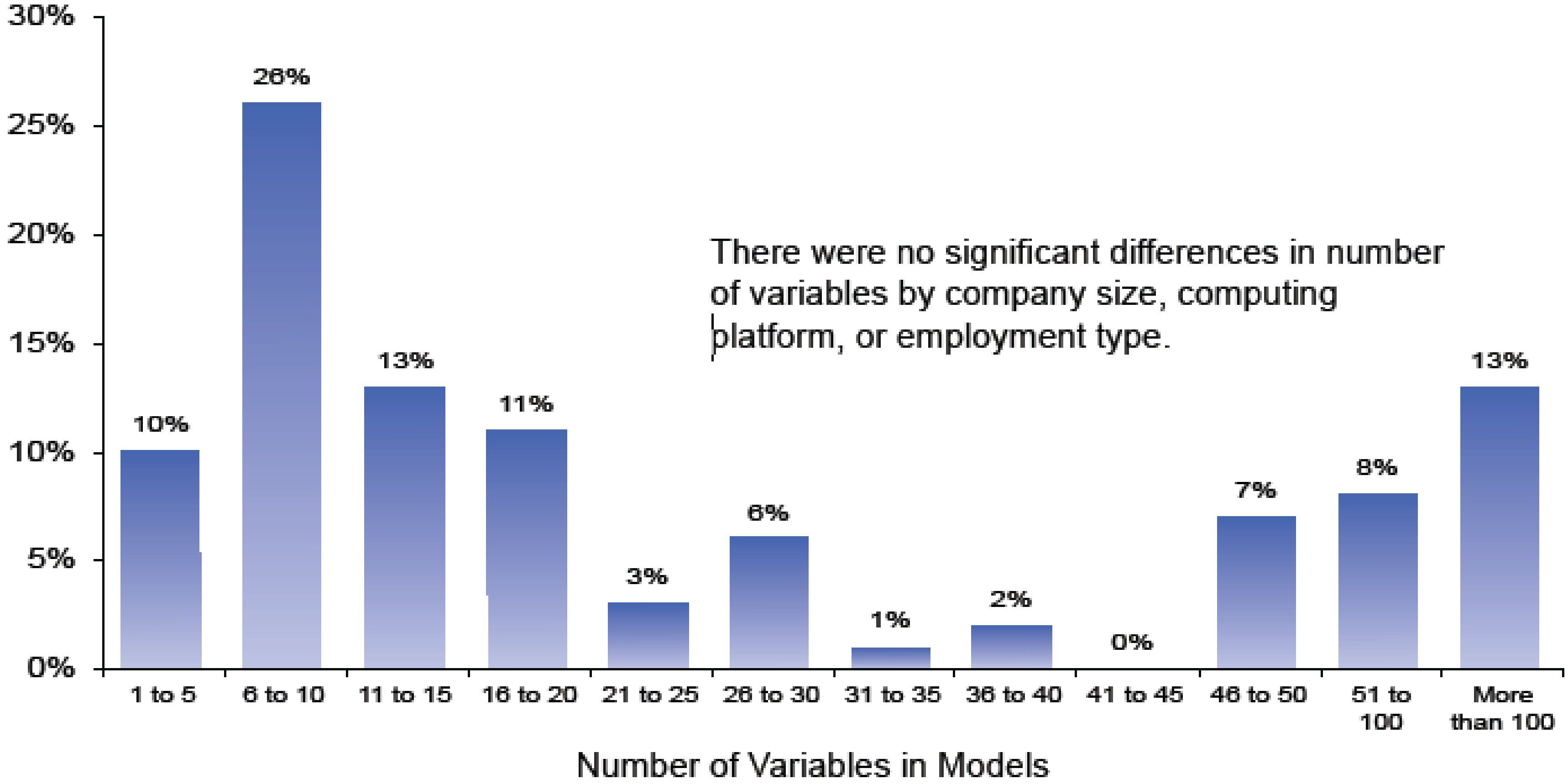


Subset Selection

- Aka feature / variable / field selection
- If there are too many attributes, select a subset that is most relevant
  - Companies often have > 2000 attributes per customer
- Subset selection was already discussed in the context of the linear regression, but is also relevant to classification in general
  - more in the context of dimensionality reduction and regularization
- Remove redundant and/or irrelevant attributes
  - Rule of thumb: keep top 50 attributes
- Automated procedures:
  - Best subset (among all exponentially many, computationally expensive)
  - Backward elimination (top down approach)
  - Forward selection (bottom up approach)
  - Stepwise regression (combines forward/backward)

Number of Variables in Final Models

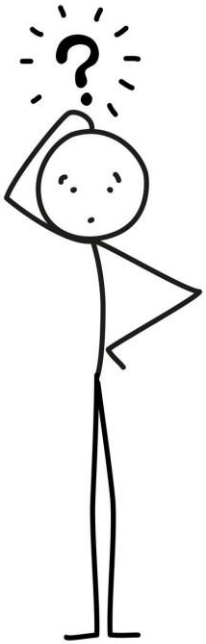
- About one-third of data miners typically build final models with 10 or fewer variables, while about 28% generally construct models with more than 45 variables.



Question: How many variables are typically incorporated into your final model?

Vendors were excluded from this analysis.

How would you define causality, and how does it differ from correlation?



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Example: The *True Advertising Lift*

1) You analyze the user journey of customers and show likely customers a display ad on a web site (treatment)
2) Actually 2.8% of those, who have seen the ad buy a car as compared to 0.1% in the group who has not seen a display ad.
3) Success!?

Is it because you showed the display ad?

We'll never know – it is *counterfactual* – for the individual

This is a problem of causal inference

Causal Inference

In many cases, we want to draw conclusions about the impact of a treatment (higher price) on an outcome (churn)

- Y~outcome (dependent variable)
- T~treatment indicator
- X~covariate (pretreatment)

What would have happened to those who, in fact, received treatment, if they have not received treatment (or vice versa)?

Correlation does not imply causation!

Causal Inference

- Y_{1i} denotes the outcome of individual i given being treated
- Y_{0i} denotes the outcome of individual i given being control
- $\Delta_i = Y_{1i} - Y_{0i}$ is the treatment effect on i

Sub.	Y_1	Y_0	Δ
A	15		
B	13		
C		8	
D		4	

Causal Inference

In a perfect world, we can observe both Y_{1i} and Y_{0i}.

- Individual treatment effect: $Y_{1i} - Y_{0i}$
- Average treatment effect: $E\ (Y_{1i} - Y_{0i})$
- Subgroup treatment effect: $E\ (Y_{1i} - Y_{0i} | X)$

Sub.	X	Y_1	Y_0	Δ
A	40	15	10	5
B	30	13	8	5
C	30	13	8	5
D	20	9	4	5

Fundamental problem of causal inference: Cannot observe both Y_{1i} and Y_{0i}.

The best we can do is to find an approximation for the potential outcome.
(see also Rubin’s causal model and work by Judea Pearl)

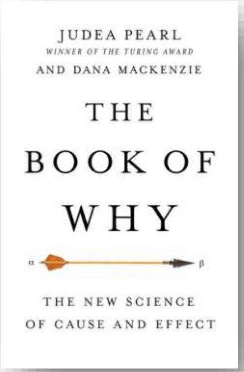
Judea Pearl on Causality

Pearl contends that until algorithms can reason about cause and effect, their utility and versatility will never approach that of humans:

*"As much as I look into what's being done with deep learning, I see **they're all stuck there on the level of associations. Curve fitting.** "*

"The key, he argues, is to replace reasoning by association with causal reasoning. Instead of the mere ability to correlate fever and malaria, machines need the capacity to reason that malaria causes fever."

Judea Pearl (ACM Fellow, Turing Award winner)



https://www.theatlantic.com/technology/archive/2018/05/machine-learning-is-stuck-on-asking-why/560675/

Internal and External Validity of a Study

- A statistical study has <u>**external validity**</u> if its inferences and conclusions can be generalized from the population and setting studied to other populations and settings.
  - Choice of training samples is important

- A statistical analysis has <u>**internal validity** if the statistical inferences about causal effects are valid</u> for the population being studied. Problems:
  - Misspecification of the functional form of the model (already discussed)
  - Measurement errors in the independent variables
  - Simultaneous causality ($x \ -> \ y$ and $y \ -> \ x$)
  - Omitted variable bias (already discussed)
  - **Sample selection bias**
    - The sample selection process influences the data and is related to the dependent variable.
    - Frequently an issue if data is not collected via a randomized controlled trials.
    - Caused by omitted variables about indivdiuals

Selection Bias and Data Collection

- **Randomized controlled trials (RCTs)** describes randomized experiments, where each subject is randomly assigned to a treated group or a control group in order to control for extraneous factors.
  - Randomization minimizes selection bias and the different comparison groups allow the researchers to determine any effects of the treatment when compared with the no treatment (control) group.
  - The **selection bias** is an issue, if data is not collected via a randomized controlled trial.

- **Quasi-experiments** (aka. natural experiments) compare natural groups and measure effects without randomization of the subjects. The independent variable (e.g., price change) is controlled, but the assignment of subjects is not random (e.g., age, ethnicity).

- **Observational studies** draw inferences from a sample to a population where the independent variable is not under the control of the researcher.

Types of Observational Studies

- **Cross-sectional study:**
  - involves data collection from a population, or a representative subset, at one specific point in time.
- **Longitudinal study:**
  - correlational research study that involves repeated observations of the same variables over long periods of time.
- **Panel (or cohort) study:**
  - a particular form of longitudinal study where a group of subjects is closely monitored over a span of time.
- **Case-control study:**
  - study in which two existing groups differing in outcome are identified and compared on the basis of some supposed causal attribute.

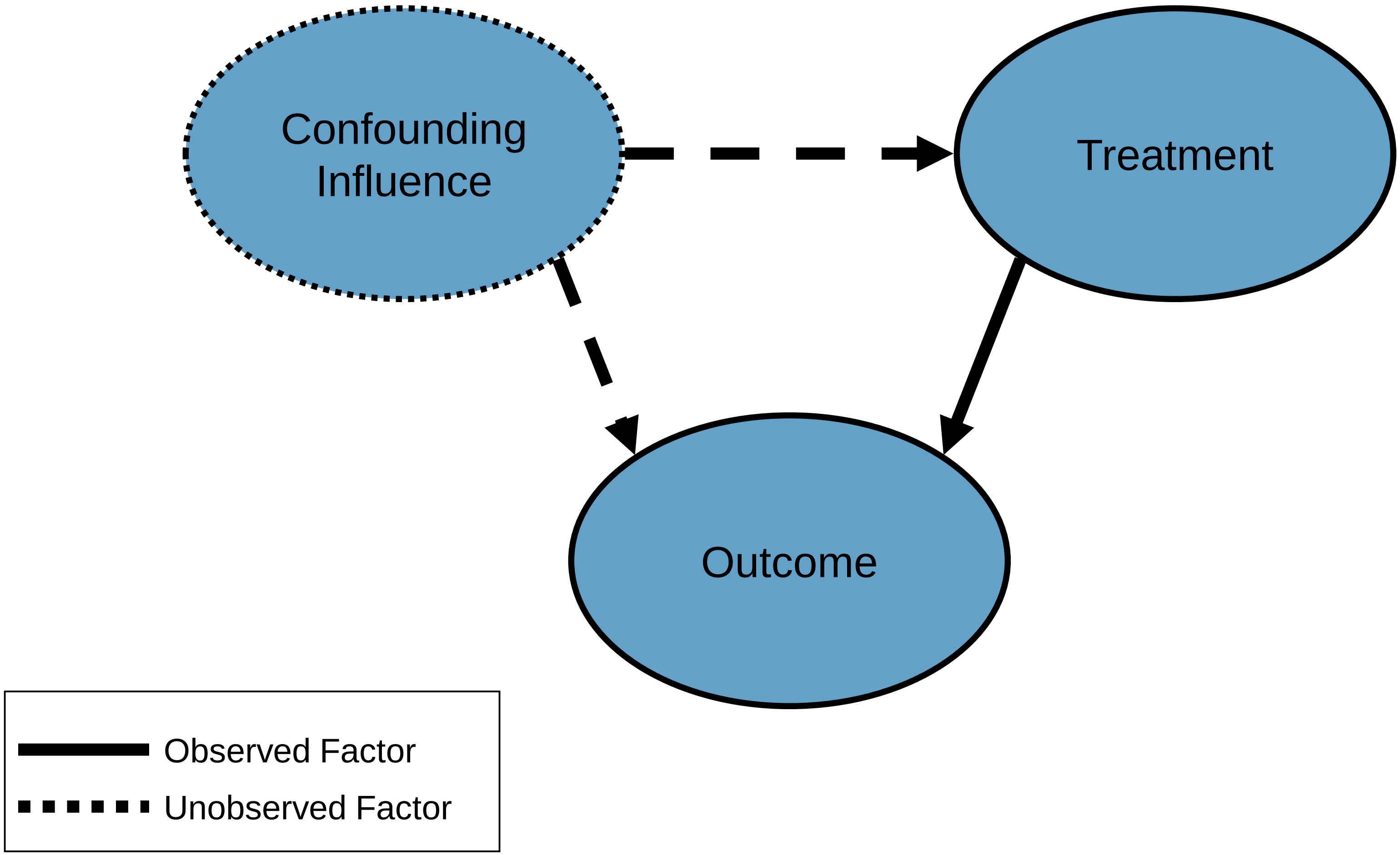
Confounding Variables

Often we have data from observational studies or quasi-experiments. Still, we want to identify causal relationships. However, there might be confounding variables:

- Confounding variable (also confounding factor, a confound, a lurking variable or a confounder) is an extraneous variable in a statistical model that correlates (directly or inversely) with both the dependent variable and the independent variable, in a way that "explains away" some or all of the correlation between these two variables.

- Remember, exogeneity was one of the Gauss-Markov assumptions in linear regression analysis.

The Problem in Causal Inference



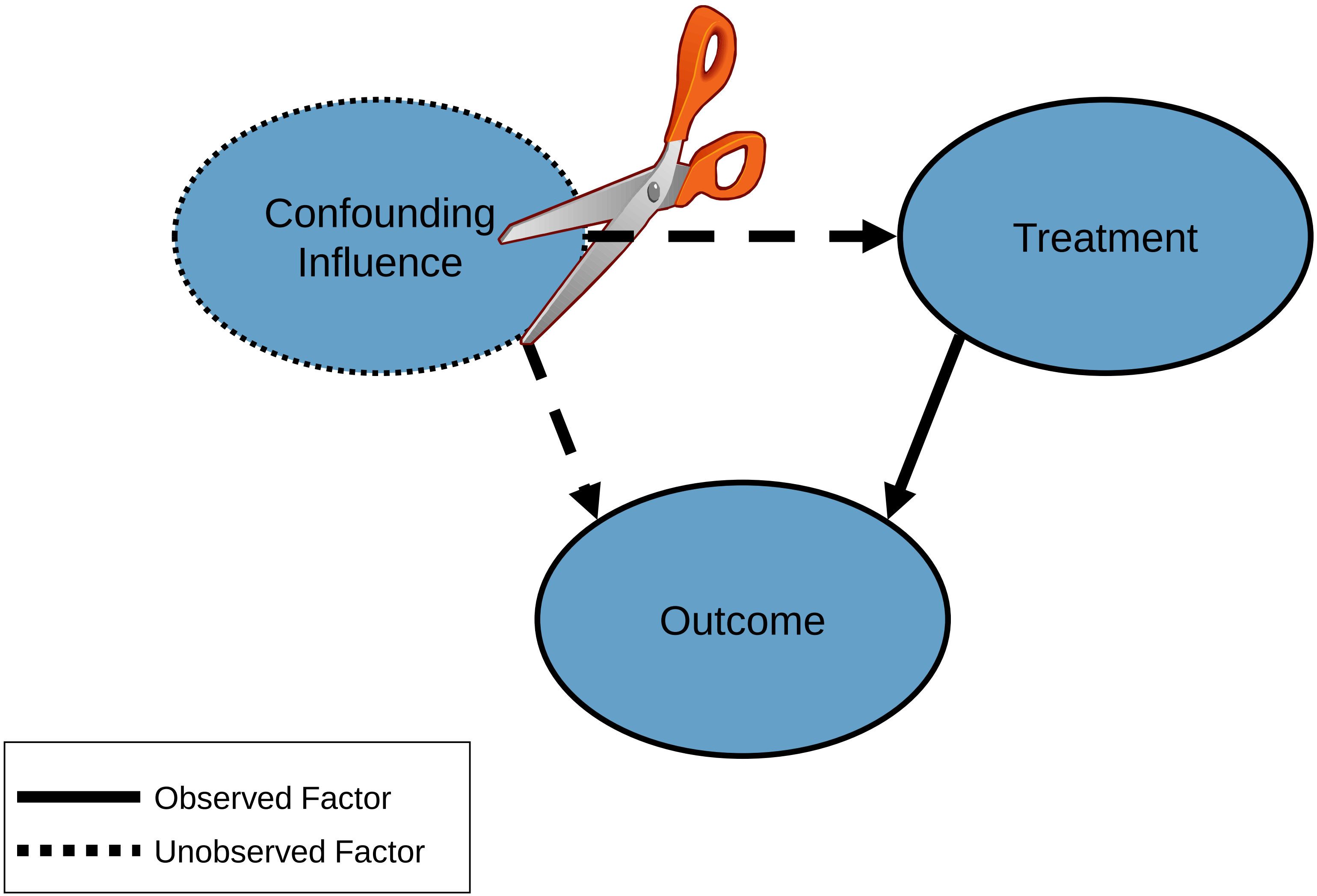
Identification Strategies

Different techniques to deal with confounding variables, i.e. to identify causal effects:

1. Randomized controlled trials (gold standard, but often not feasible)
   - can be organized in the lab or in the field
2. Fixed effects models for *panel data*
3. Difference-in-differences for *quasi-experimental data (i.e. natural experiments)*
4. Propensity score matching
5. Instrument variables

...

1. Randomized Controlled Experiments



1. Lab versus Field Experiments

Lab experiment

- create a situation with desired conditions
- manipulate some variables while controlling others
- examine the dependent variable

Field experiment

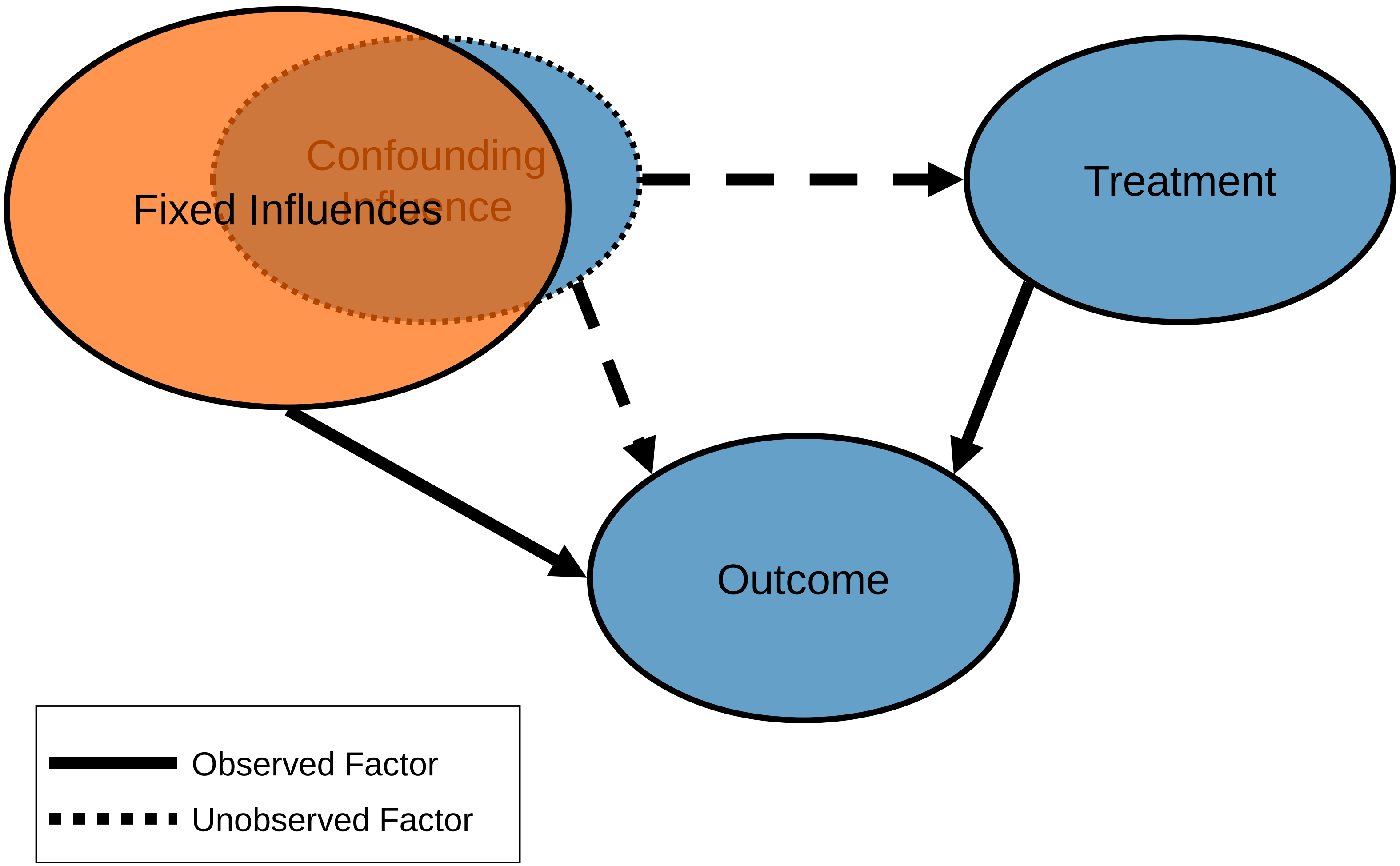
- research study in a natural setting
- manipulate some variables
- examine the dependent variable

Nowadays online services allow for large-scale field experiments! with randomized assignment of subjects to treatments (RCTs)!

Randomized controlled trials in the field address the selection bias!

	Randomized experiment	Quasi-experiment
Field	**High internal validity/ High external validity**	Low internal validity / High external validity
Lab	High internal validity/ Low external validity	Low internal validity/ Low external validity

2. Fixed Effects Models



2. Fixed Effects

Idea

- Eliminates alternative explanations that are “fixed” across units

Example

- Students with good backgrounds (family, IQ) elect to attend college, and college increases wages of a person
- If student backgrounds are not perfectly observed, there will be a residual correlation between college attendance and wages leading to a biased finding
- *Using fixed effects at the family level, we might “soak up” this influence to the extent that family quality is fixed*

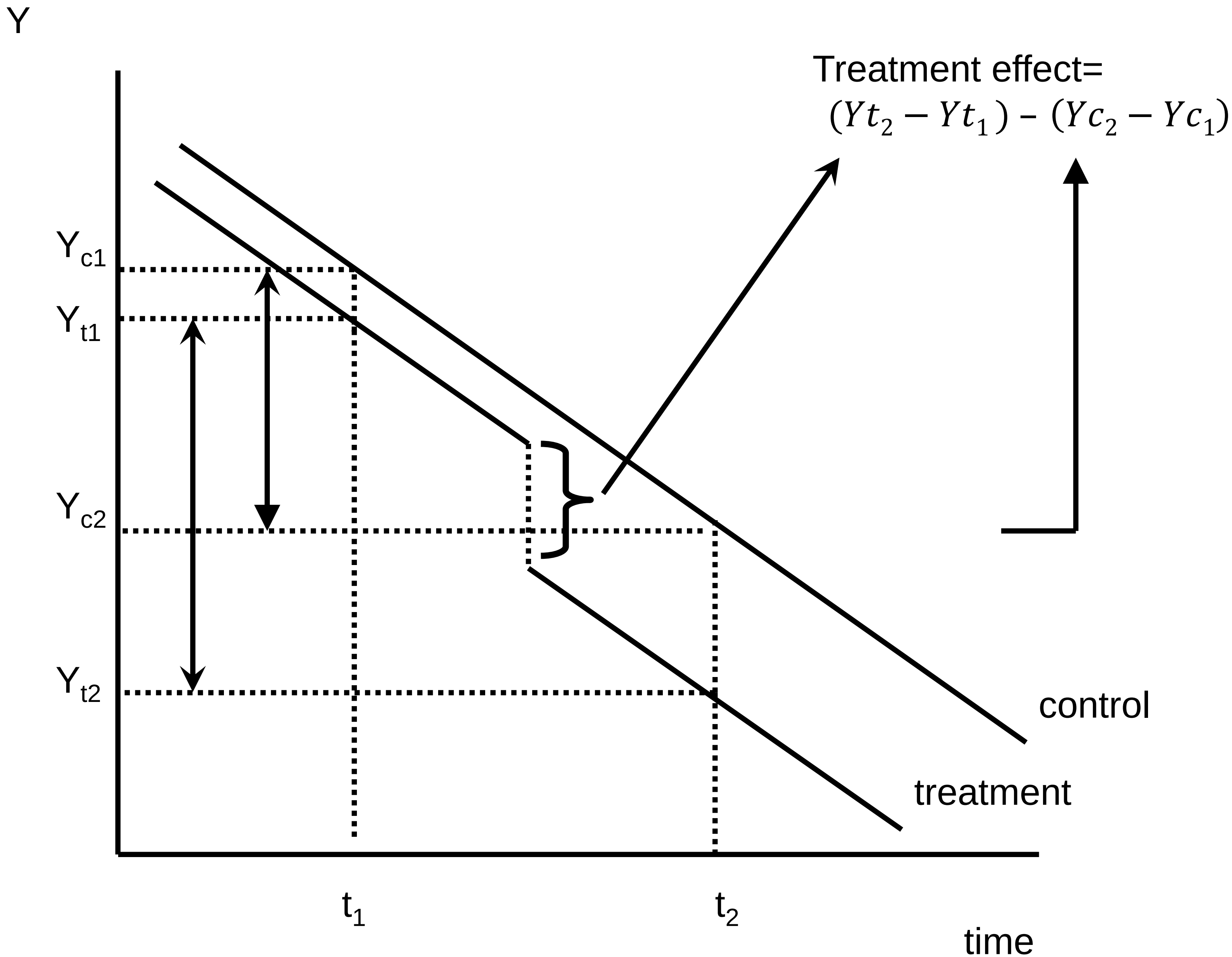
$$Wages = \beta_0 \quad + \beta_1 College + \beta_2 FamilyID + \varepsilon$$

3. Difference in Difference Models

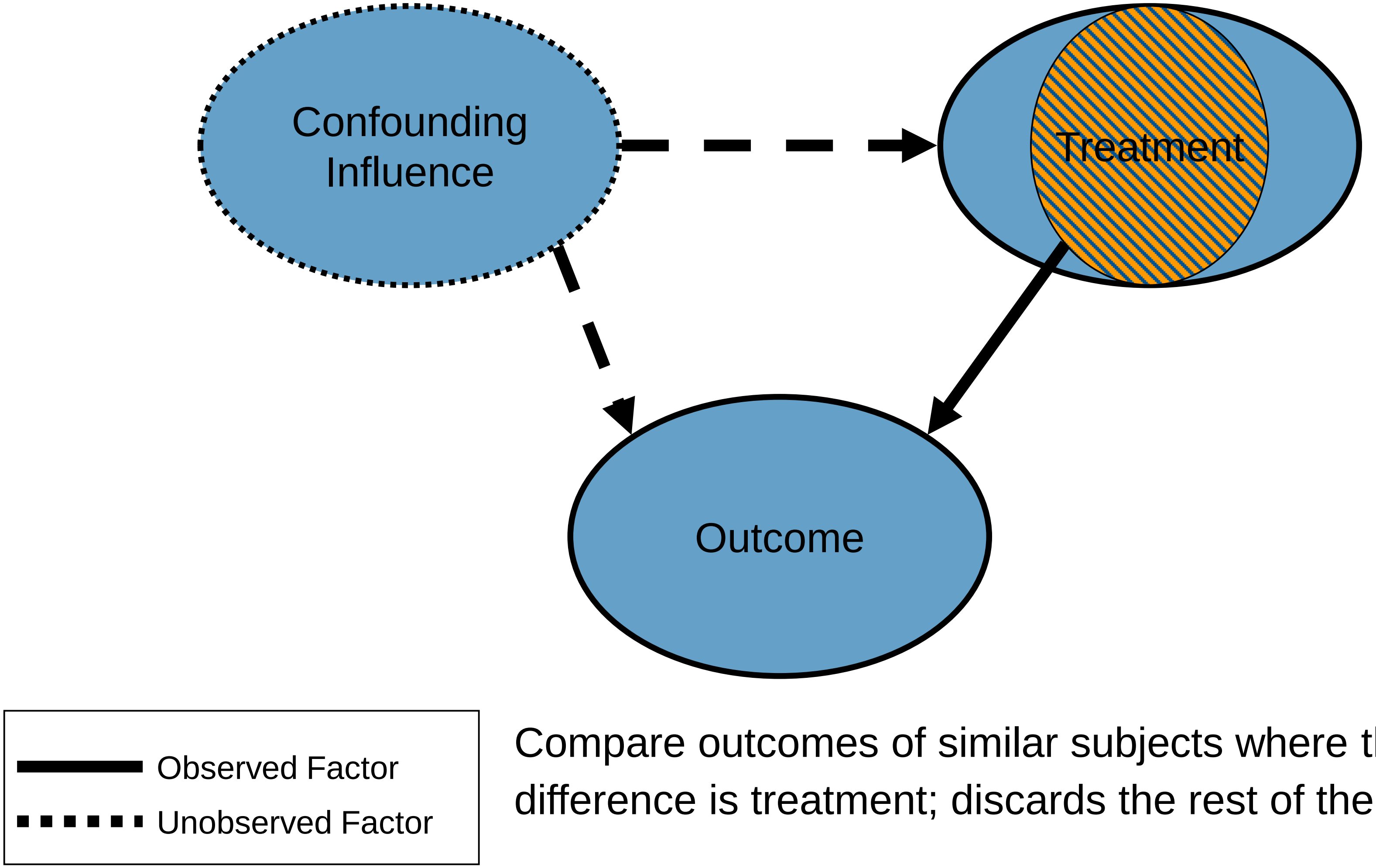
- If the treatment in a quasi-experiment is as if subjects were randomly assigned, we can use a *differences regression*. However, there might still be differences among the groups (i.e. confounding variables).
- We can take a *common trends assumption*, i.e. the treatment and control group would have the same overall trend.
- Example: Causal effect of a new law on rent control on rents for appartments per m^2. Cities w/o the new law (control) and with the new law (treatment).

Year	Treatment	Control
2019	9	10.2
2021	6.9	8.7

$$(Y_{t2} - Y_{t1}) - (Y_{c2} - Y_{c1}) = (6.9 - 9) - (8.7 - 10.2) = -0.6$$


Y
Treatment effect=
$(Yt_2 - Yt_1) - (Yc_2 - Yc_1)$
Y_{c1}
Y_{t1}
Y_{c2}
Y_{t2}
control
treatment
t_1
t_2
time

4. Propensity Score Matching (PSM)



Compare outcomes of similar subjects where the only difference is treatment; discards the rest of the subjects.

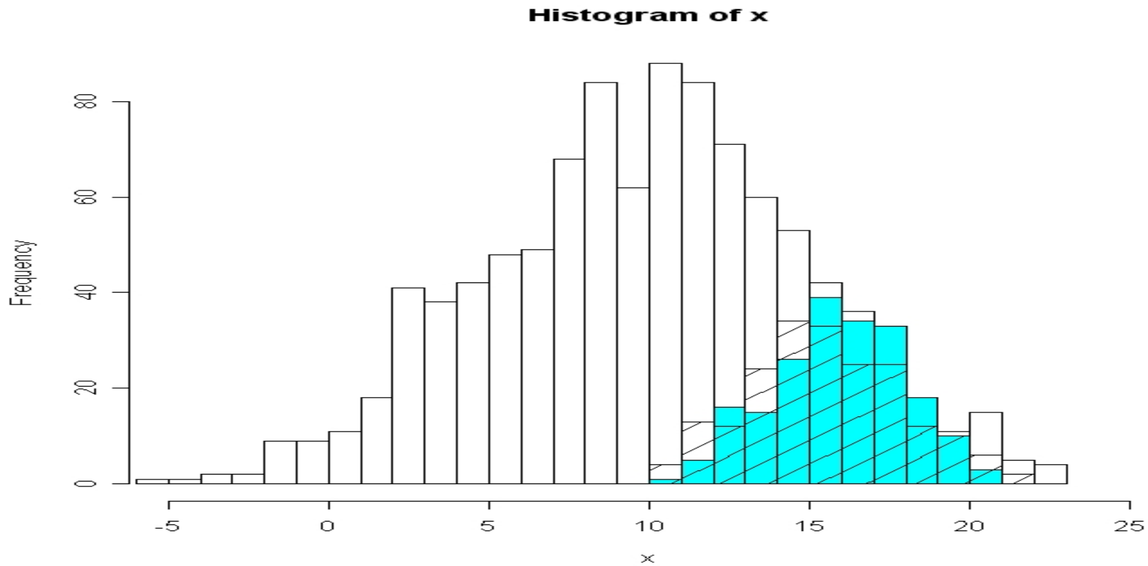
4. PSM Example: Matching

Matching to balance the covariate distribution

- To make the treated and control subject look alike before treatment
- To produce a regime which resembles a randomized experiment most, in terms of the observed covariates

Select 200 subjects in the control group, which resemble the treated most.

- Covariate X of subjects in treatment and non-treatment group have similar means. Comparison only made with matched subgroup



4. PSM Example: Standard Regression

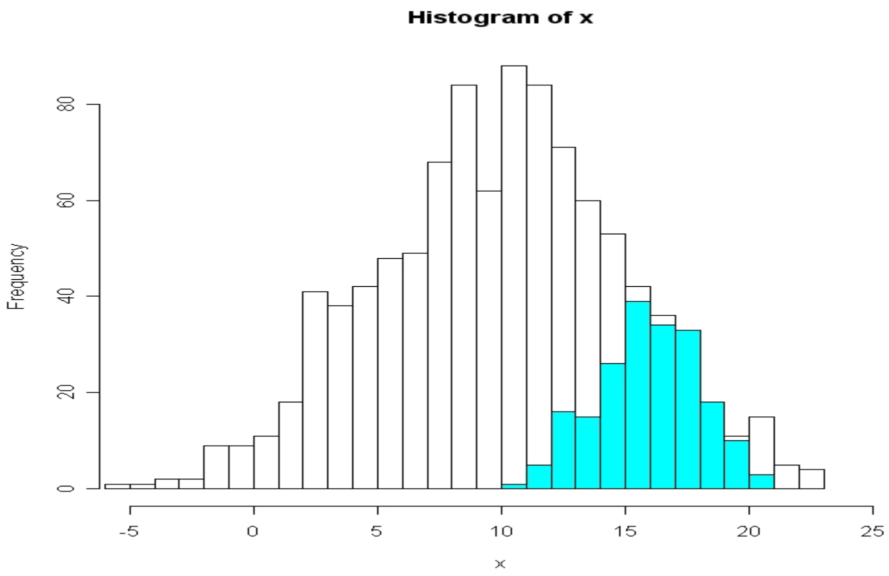
T: treatment indicator (1,0)

X: covariate, normally distributed

T=1, N(16,4), n1=200

T=0, N(10,25), n0=1000

Y: outcome



4. PSM Example: Standard Regression

Assumes subjects randomly selected into treatment!

$$Y_1 = b_0 + c \times T + b_1 \times X + \varepsilon$$

	Estimate	Std. Error	t-value	Pr(>|t|)
T	11.1549	0.4294	25.98	<2e-16 ***

Overestimates the treatment effect: Subjects with high covariate X tend to select treatment

```
> t.test(x1,x0)

t = 27.6809, df = 745.829, p-value < 2.2e-16

95 percent confidence interval:
 5.515863 6.357964

sample estimates:
mean of x mean of y
15.885911  9.948997
```

4. Propensity Score Matching

1. Estimate propensity score
   - The likelihood/propensity of an individual being selected in the treatment
   - Often done via logistic regression

2. Match subjects with similar propensity score
   - Matching algorithm (e.g., nearest neighbour) iteratively finds the pair of subjects with the shortest distance. The goal is to balance the pretreatment covariates distribution

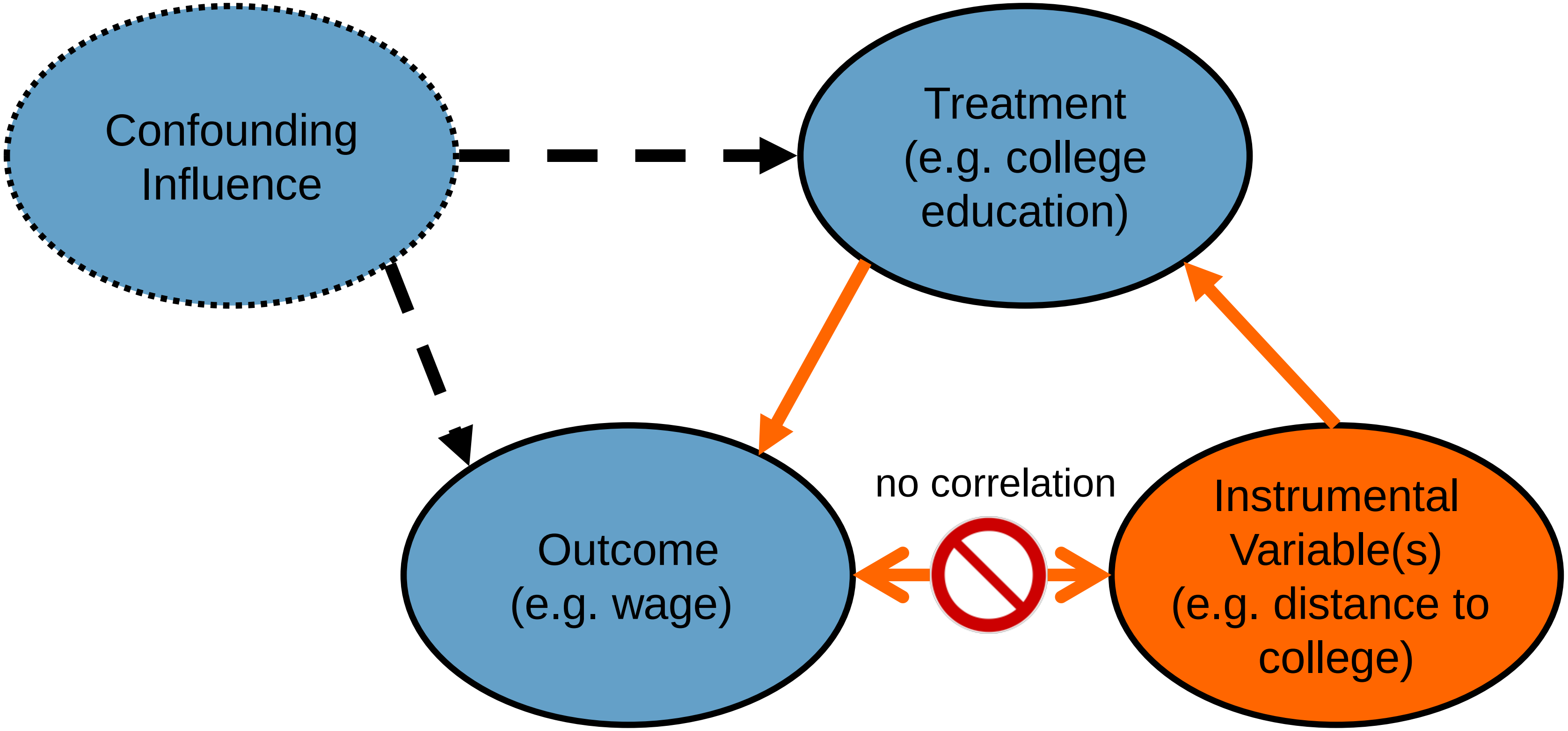
3. Evaluate quality of matching
   - Check if the treatment and comparison group are similar across observable characteristics

4. Evaluate outcomes
   - based on the treatment and the matched comparison group

5. Instrumental Variables (IV)

- We try to understand the impact of college education on wages
  - Students with good ability (effort, IQ) elect to attend college, and college increases wages. Ability is a confounder but cannot always be observed.
- We assume that the instrument DOES NOT have a causal effect on outcome, but assume the instrument DOES have a causal effect on the treatment variable
  - Distance to college could be an instrument variable. It influences whether students go to college, but is uncorrelated with the wages.
- The Instrument (distance to college) is randomly assigned to individuals.
- The causal effect of the instrument on the treatment is their correlation.
- Since the instrument is randomly assigned, it is not correlated with any other possible confounders, except the treatment.
  - We substitute actual college attendance with college attendance predicted by observables (e.g., distance to college).
- Estimation via 2-stage least squares (2SLS)

5. Instrumental Variables



$$\widehat{Col.Edu.} = \beta_0 \ + \beta_1 DistanceToCollege + \varepsilon$$

$$Wage = \beta_2 \ + \beta_3 \widehat{Col.Edu.} + \varepsilon$$

If β_3 is significant, then there is causation between the treatment and the outcome

Empirical Evidence: A Recent Study on Ad Lift

Gordon, Brett, et al. "A Comparison of Approaches to Advertising Measurement: Evidence from Big Field Experiments at Facebook." (Marketing Science, 2019)

We examine how common techniques used to *measure the causal impact* of ad exposures on users' conversion outcomes compare to the "gold standard" of a true experiment (*randomized controlled trial*). Using data from 12 US advertising lift studies at Facebook comprising 435 million user-study observations and 1.4 billion total impressions we *contrast the experimental results* to those obtained from *observational methods*, such as comparing exposed to unexposed users, matching methods, model-based adjustments, synthetic matched-markets tests, and before-after tests.

- We show that observational methods often fail to produce the same results as true experiments even after conditioning on information from thousands of behavioral variables and using non-linear models.
- Our findings suggest that common approaches used to measure advertising effectiveness in industry fail to measure accurately the true effect of ads.