MSML610: Advanced Machine Learning

Causal Inference

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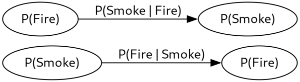
References:

- Easy:
  - Hurwitz, Thompson: Causal Artificial Intelligence: The Next Step in Effective Business AI, 2024
- Medium / Difficult
  - AIMA
  - Facuce

- ***Causal Networks***
    - Variables
    - Intervention
    - Type of Variables in Causal AI
    - Paths

(Non-Causal) Bayesian Networks

- **Bayesian networks** represent a joint distribution function
  - The direction of the arrow represent **conditional dependence** (not causality)
    - $A \rightarrow B$ requires to estimate $\Pr(A|B)$
  - There are many possible **edges** and **node ordering** for the same Bayesian network
- E.g., a Bayesian network with *Fire* and *Smoke*, which are dependent
  - $Fire \rightarrow Smoke$
    - Need $\Pr(Fire)$ and $\Pr(Smoke|Fire)$ to compute $\Pr(Fire, Smoke)$
  - $Smoke \rightarrow Fire$
    - Need $\Pr(Smoke)$ and $\Pr(Fire|Smoke)$
  - Networks are equivalent and convey the same information
  - Different difficulties to estimate



- There is an **asymmetry in nature**
  - Extinguishing fire stops smoke
  - Clearing smoke doesn't affect fire

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Causal (Bayesian) Networks

- **Causal networks** are Bayesian networks forbidding **non-causal edges**
- Use judgment based on nature instead of just statistics
  - E.g., from *"Are random variables Smoke and Fire correlated?"* to *"What causes what, Smoke or Fire?"*
- **"Dependency in nature" is like assignment in programming**
  - E.g., nature assigns *Smoke* based on *Fire*:
    - ✅ $Smoke := f(Fire)$
    - ❌ $Fire := f(Smoke)$
  - Structural equations describe "assignment mechanism" in causal graphs

$$X_i := f(X_j) \iff X_j \rightarrow X_i$$

Causal DAG

- **Causal DAG**
  - *Directed*: Arrows show direction of cause $\rightarrow$ effect
  - *Acyclic*: No feedback loops
    - Causal relationships assume a temporal order: cause happens before effect
    - A cycle would imply a variable is both a cause and effect of itself (paradox)
- **Benefits**
  - DAGs encode *causal* rather than *associative* links
  - Enables reasoning about interventions and counterfactuals
  - Supports explainable AI models
  - Stability to conditional probability estimation
- **Limitations**
  - Requires domain knowledge to specify structure
  - Assumes all relevant variables are included (e.g., no hidden confounders)

Causal Edges are Stable

- **Causal edge** $X \rightarrow Y$ shows direct causal influence of X on Y, holding other variables constant
  - Captures how manipulating X changes Y, not just their covariance
- Causal edges reflect **stable relationship**
  - Mechanistic stability
    - Causal relationships show system function, not just behavior in one dataset
    - E.g., "Temperature $\rightarrow$ ice melting rate" holds true in Alaska and Arizona
  - Invariance under interventions
    - If X causes Y, intervening on X affects Y consistently, despite confounders or context changes
  - Easier estimation through causal modeling
    - Identifying causal direction focuses estimation on effect size (e.g., regression of Y on X under intervention)
  - Reduced sensitivity to sampling and omitted variables
    - Correlations may change with confounder addition or removal
    - True causal edge persists, stable across model specifications
- **Example**: study *Exercise* $\rightarrow$ *Health*:
  - Correlation may differ in young or elderly populations
  - Causal effect remains stable, as physiological mechanism doesn't change

Structural Causal Model

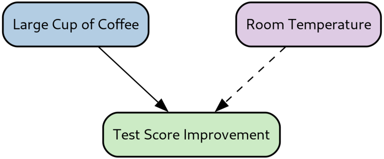
- A **Structural Causal Model** (SCM) translates a causal DAG into mathematical equations
  - DAGs show structure (variables and arrows)
  - SCMs use equations to define how variables interact
- **Structure of SCMs**
  - Variables $X_1, X_2, ..., X_n$ represent quantities in the system
  - Equations model each variable as a function of its direct causes
  - Formally, X_i is modeled as:

$$X_i = f_i(Parents(X_i), \varepsilon_i)$$

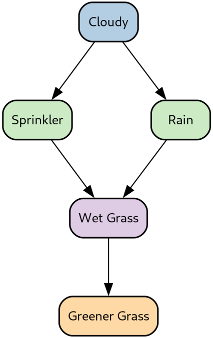
    where:
    - $Parents(X_i)$ are direct causes of X_i
    - ε_i is an exogenous (external, unobserved) noise term
- **Properties**
  - Explain causal relationships between variables
  - Provide a foundation for causal reasoning and simulation
  - Describe how the world works, not just variable correlations

Structural Causal Model: Example

- **Explanatory variables**
  - You can manipulate or observe when changes are applied
  - E.g., *"does a large cup of coffee before an exam help with a test?"*
- **Outcome variables**
  - Result of the action
  - E.g., *"by how much did the score test improve?"*
- **Unobserved variables**
  - Not seen or more difficult to account
  - E.g., *"temperature of the room makes students sleepy and less alert"*



Structural Causal Model: Sprinkler Example



- Structural equations for this model:

$$\begin{cases} C := f_C(\varepsilon_C) \\ R := f_R(C, \varepsilon_R) \\ S := f_S(C, \varepsilon_S) \\ W := f_W(R, S, \varepsilon_W) \\ G := f_G(W, \varepsilon_G) \end{cases}$$

- Unmodeled variables ε_x represent error terms
  - E.g., ε_W is another source of wetness besides *Sprinkler* and *Rain* (e.g., *MorningDew*)
- Assume unmodeled variables are exogenous, independent, with a certain distribution (prior)

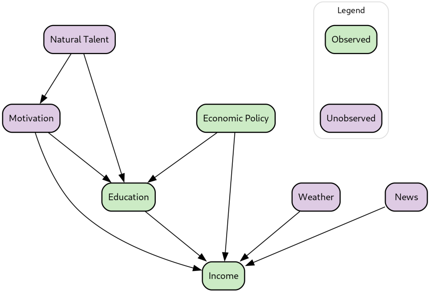
- Express joint distribution of five variables as a product of conditional distributions using causal DAG topology:

$$\Pr(C, R, S, W, G) = \Pr(C)\Pr(R|C)\Pr(S|C)\Pr(W|R, S)\Pr(G|W)$$

- Causal Networks
  - ***Variables***
  - Intervention
  - Type of Variables in Causal AI
  - Paths

Observed Vs. Unobserved Variables

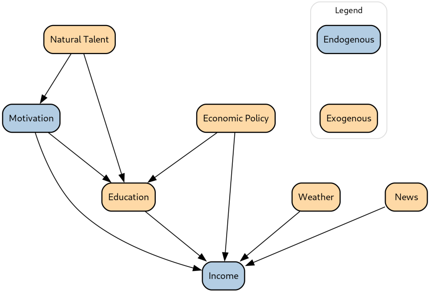
- **Observed variables**
  - Aka "measurable" or "visible"
  - Variables directly measured or collected in a dataset
  - E.g.,
    - Education
    - Income
    - Blood pressure
    - Product price



- **Unobserved variables**
  - Aka "latent" or "hidden"
  - Exist but not measured or included in data
  - E.g.,
    - Natural talent
    - Motivation
    - Company culture
  - Ignoring unobserved variables distorts causal relationships
    - Observed: *IceCreamSales* and *DrowningRates*
    - Unobserved: *Temperature*
    - Misleading conclusion: *IceCream* causes *Drowning*

Endogenous Vs. Exogenous Variables

- **Endogenous variables**
  - Values determined *within* the model
    - Dependent on other variables in the system
  - Represent system's internal behavior and outcomes
  - E.g.,
    - Motivation
    - Income



- **Exogenous variables**
  - Originate *outside* the system being modeled
    - Not caused by other variables in the model
  - Represent background conditions or external shocks
  - E.g.,
    - Natural talent
    - Economic policy
    - Weather
    - News

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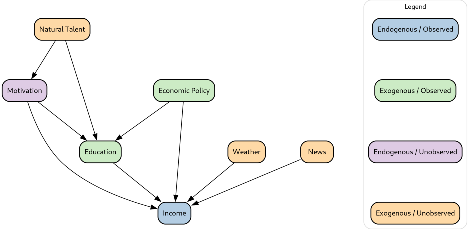
Endo / Exogenous, Observed / Unobserved Vars

- In **Structural Causal Models**

$$X_i = f_i(Parents(X_i), \varepsilon_i)$$

where:
  - X_i: endogenous
  - ε_i: exogenous noise
- **Typically**
  - *Endogenous variables*: focus for prediction and intervention
  - *Exogenous variables*: capture randomness or unknown external factors



Variable Type	Observability	Example
Endogenous	Observed	Income
Exogenous	Observed	Education
Endogenous	Unobserved	Motivation
Exogenous	Unobserved	Natural Talent

- Causal Networks
    - Variables
    - ***Intervention***
    - Type of Variables in Causal AI
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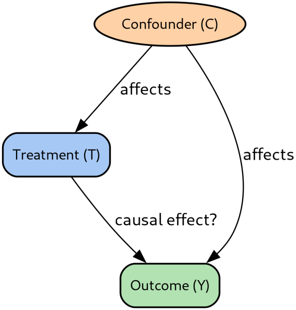
Estimating Causal Effects

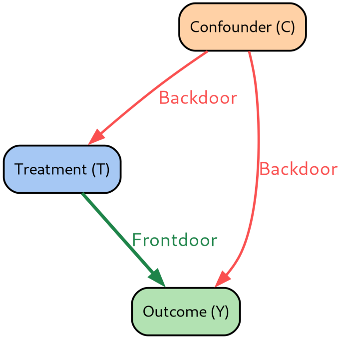
- **Goal**: Determine the causal effect of a treatment variable (aka intervention) T on an outcome Y
- **Example:**
  - T = *"takes drug"*
  - Y = *"recovers"*
  - C = *"overall health"*
- Healthier people may take medicine and recover faster $\implies$ correlation without causation
- In **observational data**
  - Confounding variable C affects both treatment T and outcome Y
  - C creates *spurious correlation* between T and Y



- **Problem**
  - There is a "backdoor path" *Treatment* $\leftarrow$ *Confounder* $\rightarrow$ *Outcome*

Frontdoor and Backdoor Paths: Intuition

- A **backdoor path** is any path from T to Y starting with an arrow into T
  - E.g., $T \leftarrow C \rightarrow Y$
  - Interpretation:
    - C is a common cause of T and Y, confounding their relationship
    - Controlling (conditioning) for C blocks the backdoor path, identifying the causal effect of T on Y



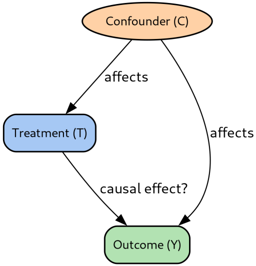
- A **frontdoor path** goes directly or indirectly from T to Y through mediators, following causal flow
  - E.g., $T \rightarrow Y$
  - Interpretation:
    - Direct causal path of interest
    - No mediators, so front-door path is direct causal effect of T on Y

Randomized Controlled Trials (RCTs)

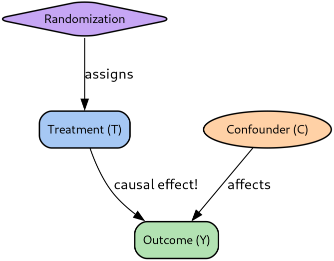
- **Randomized Controlled Trial** is an experimental study to assess causal effect of an intervention or treatment
  - Determine whether an intervention causes an effect, not just associated with it
  - Eliminate selection bias and confounding variables through randomization
- **Key Components**
  - *Randomization*: ensures groups are statistically equivalent at baseline
  - *Control Group*: receives a placebo or standard treatment
  - *Blinding*: participants and/or researchers do not know the assignment to avoid bias
  - *Outcome Measurement*: pre-defined metrics assess the intervention's effect
- **Example**: testing a new drug
  - Treatment group receives the new drug
  - Control group receives a placebo
  - Compare recovery rates after a fixed period
- **Pros**
  - Provides clear causal inference due to randomization
- **Cons**
  - Expensive and time-consuming
  - Ethical or practical constraints may prevent randomization

RCTs Solve the Problem of Confounders

- In **observational data**
  - Confounding variable C affects both treatment T and outcome Y
  - C creates *spurious correlation* between T and Y



- In **experimental settings**
  - Randomization (R) breaks link between C and T
  - Random assignment prevents influence on both treatment and outcome
  - T is independent of C: $T \perp C$
  - Only open path between T and Y is causal path $T \rightarrow Y$



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Causal Graphs and Interventions

- **Observing correlations** between variables *does not reveal causality*
  - $\Pr(Y|T)$ confounds direct and indirect influences
- **Randomized Controlled Trials** provide the *gold standard* for causal inference
  - Randomization breaks all back-door (confounding) paths
  - RCTs are expensive, slow, or ethically impossible
- **Alternative solution**
  - Can we estimate the *causal effect* from *observational data alone*?
  - Under *what conditions* and using *which variables*?
- **Idea**: Identify and condition on the right *confounders* to:
  - Block spurious associations between T and Y
  - Recover the true causal effect $\Pr(Y|do(T))$

Intervention in Structural Equations

- **Purpose of Structural Equations**
  - Capture causal mechanisms among variables
  - Predict impact of external interventions
- **Effect of Intervention** $do(X_j = x_j)$
  - Original equation:
$$X_j = f_j(Parents(X_j), \varepsilon_j)$$
  - Modified by intervention:
$$X_j = x_j \text{ (fixed value)}$$
  - "Mutilate" causal network by *removing incoming edges* to X_j
  - Recompute joint distribution of all variables using modified structure
- **Intuition**
  - *do*-operator enforces variable's value externally, breaking causal dependencies
  - Enables reasoning about "what would happen if...?" scenarios

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Adjustment Formula in Causal Networks

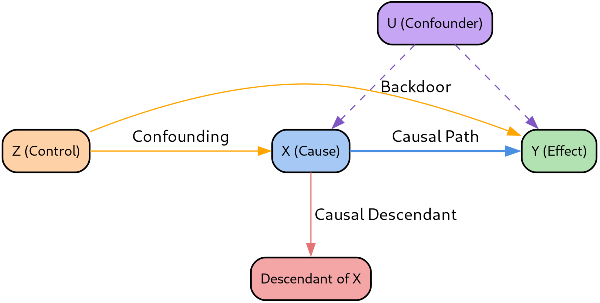
- **Goal**
  - Estimate causal effect of intervention $do(X_j = x_{jk})$ on another variable X_i
- **The Adjustment Formula**
  - Derived from the post-intervention joint distribution:

$$\Pr(X_i = x_i | do(X_j = x_j^*)) = \sum_{Parents(X_j)} \Pr(x_i | x_j^*, Parents(X_j)) \Pr(Parents(X_j))$$

  - The mechanism for X_j is *removed*: it is treated as a fixed cause, not a random variable
- **Interpretation**
  - Computes a *weighted average* of effects of X_j and its parents on X_i
  - Weights come from prior probabilities of the parents' values
- **Back-Door Criterion**
  - A set Z is a valid adjustment set if it blocks *all back-door paths* from X_j to X_i
  - Ensures $X_i \perp \text{Parents}(X_j) | X_j, Z$
- **Why It Matters**
  - Enables causal inference from observational data
  - Estimate treatment and policy effects *without randomized trials*

Backdoor Criterion: Definition

- A set of variables Z satisfies the **backdoor criterion** for variables X (cause) and Y (effect) in a causal graph if:
  1. **No element of Z is a descendant of X**
     - Ensures Z does not "block" part of the causal effect of X on Y
     - Descendants of X may carry information about the causal effect and should not be controlled for
  2. **Z blocks every path between X and Y containing an arrow into X**
     - These paths are *backdoor paths*, representing potential confounding influences
     - Blocking them ensures any remaining association between X and Y is causal, not spurious



Backdoor Criterion: Intuition

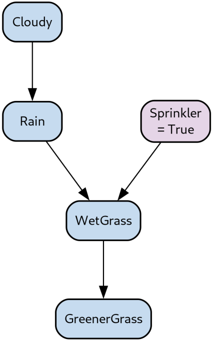
- **Intuition**:
  - The goal is to isolate the causal effect of X on Y by eliminating *confounding bias*
  - Controlling for an appropriate set Z makes the relationship between X and Y as if X were randomly assigned
- **Application**:
  - When Z satisfies the backdoor criterion, we can estimate causal effects from **observational data** (without experiments)
  - The causal effect can be computed using:

$$\Pr(Y|do(X)) = \sum_z \Pr(Y|X, Z = z)P(Z = z)$$

Intervention: Sprinkler Example

- "Intervene" by turning the sprinkler on
  - In do-calculus $do(Sprinkler = T)$
  - Sprinkler variable s is independent of cloudy day c
- Structural equations after intervention:

$$\begin{cases} C := f_C(\varepsilon_C) \\ R := f_R(C, \varepsilon_R) \\ S := True \\ W := f_W(R, S, \varepsilon_W) \\ G := f_G(W, \varepsilon_G) \end{cases}$$



- $\Pr(S|C) = 1$ and $\Pr(W|R,S) = \Pr(W|R, S = T)$ and the joint probability becomes:

$$\Pr(C, R, W, G | do(S = True)) = \Pr(C)\Pr(R|C)\Pr(W|R, S = True)\Pr(G|W)$$

- Only descendants of manipulated variable *Sprinkler* are affected

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Intervention vs. Observation in Causal Models

- **Intervention** conceptually *breaks* normal causal dependencies
  - Intervening on *Sprinkler* removes causal link from *Weather* to *Sprinkler*
  - After intervention, causal graph excludes arrow $Weather \rightarrow Sprinkler$
  - *Weather* and *Sprinkler* become independent under intervention
- **Observation vs. Intervention**
  - **Observation**: seeing $Sprinkler = T$
    - Expressed as $\Pr(\cdot|Sprinkler = T)$
    - Reflects *passive observation* — sprinkler on provides information about weather
    - Since *Weather* influences *Sprinkler*, observing $Sprinkler = T$ makes it *less likely Weather* is cloudy
  - **Intervention**: forcing $Sprinkler = T$
    - Expressed as $\Pr(\cdot|do(Sprinkler = T))$
    - *Active manipulation* — set sprinkler on regardless of weather
    - Causal link from *Weather* to *Sprinkler* is cut, weather distribution remains unchanged
- **Key intuition**
  - Observation $\rightarrow$ correlation (information flows along causal links)
  - Intervention $\rightarrow$ causation (links into manipulated variable are removed)
  - Thus, $\Pr(Weather|Sprinkler = T) \neq \Pr(Weather|do(Sprinkler = T))$

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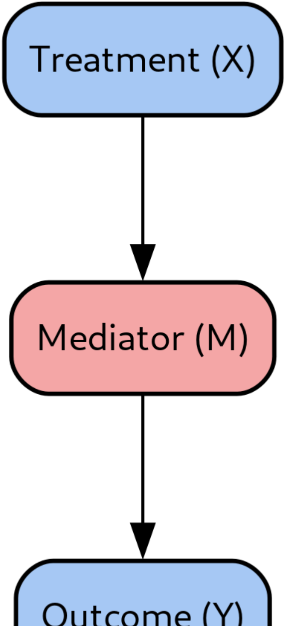
Controlling for a Variable in Causal Analysis

- **Definition**
  - To *control* a variable means to hold it constant (statistically or experimentally) to isolate the causal effect of another variable
- **Example**
  - Does exercise (X) cause weight loss (Y)?
  - Confounder: Diet (Z) affects both exercise and weight
  - By controlling for diet (e.g., comparing people with similar diets), you can estimate the effect of exercise more accurately
- In **regression analysis**
  - Include Z as an additional independent variable
  - E.g., in $Y = \beta_0 + \beta_1 X + \beta_2 Z + \varepsilon$
    - β_1 measures the effect of X *controlling for* Z
    - Coefficient $\beta_1 =$ *change in* Y with a one-unit change in X_1, *holding* X_2 *constant*
    - Isolates X_1's unique contribution
    - Compares individuals with the same X_2 but different X_1
- In **experiments**
  - Keep Z constant or randomize it

- Causal Networks
  - Variables
  - Intervention
  - ***Type of Variables in Causal AI***
  - Paths

Mediator Variable

- A **mediator variable** M is an intermediate variable that *transmits* the causal effect from X (treatment) to Y (outcome)
  - Lies **on the causal path** between X and Y
  - Captures the **mechanism or process** through which X influences Y



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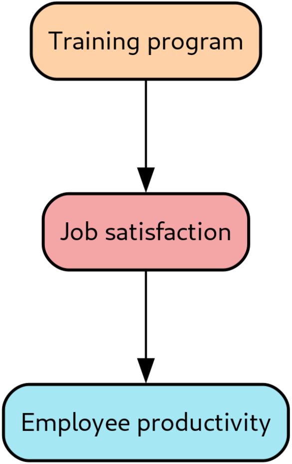
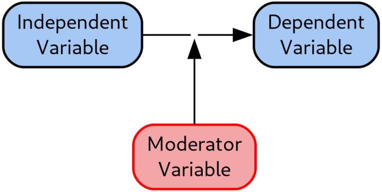
Mediator Variable: Example

- Research question: does a *training program* increase *employee productivity*?
- The causal effect may be **indirect**, operating through a **mediator**
  - The training program might not immediately boost productivity
  - Instead, it could enhance **job satisfaction**, which in turn raises productivity
- **Causal interpretation**
  - X: Training Program (cause)
  - M: Job Satisfaction (mediator)
  - Y: Employee Productivity (effect)
  - Path: $X \to M \to Y$
- **Direct vs. Indirect effects**
  - *Indirect effect* X affects Y through M
  - *Direct effect* X affects Y not through M
  - Controlling for M separates these two effects, clarifying *how* training impacts outcomes



Moderator Variable

- A **moderator variable** changes the *strength* or *direction* of the relationship between an independent variable (X) and a dependent variable (Y)
  - Moderator is not part of the causal chain but conditions the relationship



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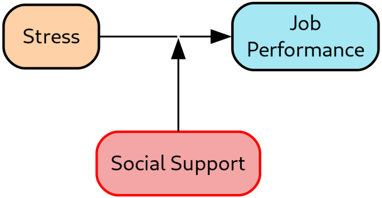
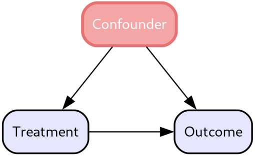
Moderator Variable: Example

- Research question: study relationship between stress X and job performance Y
- Social support M as a moderator
  - High social support weakens stress's negative effect on performance
  - Low social support strengthens stress's negative effect on performance



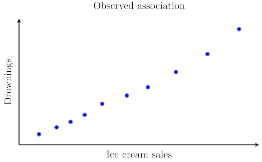
Confounder Variable

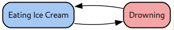
- A **confounder**
  - Influences multiple variables in a causal graph
  - Affects both treatment (cause) and outcome
  - Creates misleading association if not controlled



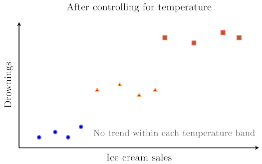
Confounder Variable: Example

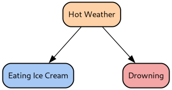
- *IceCreamSales* and *Drowning* move together
  - Correlation-based model claims association, but how to use this relationship?
  - Ban ice cream to prevent drowning?
  - Ice cream maker increase drowning to boost sales?

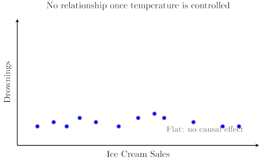




- In reality, no cause-effect between *IceCreamSales* and *Drowning*
  - *Temperature* is a confounder
  - When controlling for season in regression or intervention, association disappears

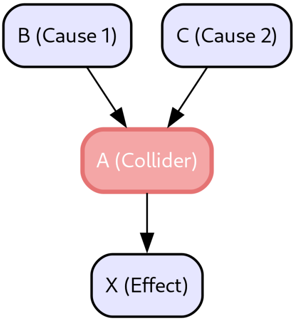






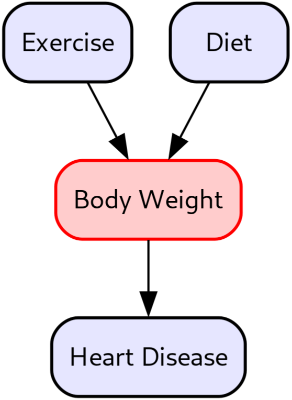
Collider

- A **collider** is a variable A influenced by multiple variables
  - In a causal graph A with incoming edges from variables B, C
- A collider complicates understanding relationships between variables B, C and those it influences, X



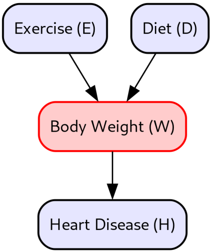
Collider: Examples

- Study the relationship between *Exercise* and *HeartDisease*
  - *Diet* and *Exercise* influence *BodyWeight*
  - *BodyWeight* influences *HeartDisease*
  - *BodyWeight* is a collider



Collider Bias

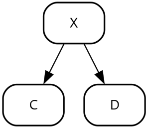
- Aka "Berkson's paradox"
- Conditioning on a collider can introduce a spurious association between its parents by *"opening a path that is blocked"*
- Consider the variables:
  - *Diet* (D)
  - *Exercise* (E)
  - *BodyWeight* (W)
  - *HeartDisease* (D)
- **Without conditioning on W**
  - E and D are independent
    - E.g., knowing someone's exercise level E doesn't give information about diet D, and vice versa
  - The collider W blocks any association between E and D
- **After conditioning on W**
  - E.g., looking for individuals with specific body weight
  - You introduce a dependency between E and D
  - Since W is fixed, any change in E must be balanced by a change in D to maintain the same



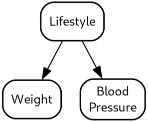
- Causal Networks
  - Variables
  - Intervention
  - Type of Variables in Causal AI
  - ***Paths***

Fork Structure

- A **fork** occurs when a single variable causally influences two or more variables
  - Formally: $X \to C$ and $X \to D$
- X is a common cause (confounder) of C and D
- Forks induce statistical dependence between C and D
  - Even if C and D are not causally linked
- Conditioning on X blocks the path and removes spurious correlation



- Example:
  - Lifestyle factors as confounders
  - *Lifestyle* affects both *Weight* and *BloodPressure*
  - These outcomes may appear correlated due to shared cause



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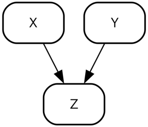
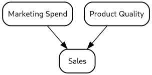
Inverted Fork

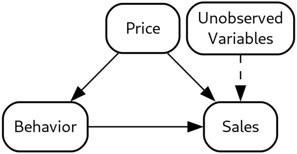
- An **inverted fork** occurs when two or more arrows converge on a common node
  - Also known as a **collider**
- Colliders block associations unless the collider or its descendants are conditioned on
- Conditioning on a collider "opens" a path, inducing spurious correlations
  - This is the basis of selection bias
- Example:
  - Sales influenced by multiple independent causes
  - *MarketingSpend* and *ProductQuality* both influence *Sales*
  - Conditioning on *Sales* can induce false dependence between *MarketingSpend* and *ProductQuality*





Path connecting unobserved variables

- **Unobserved variables** affect the model but we don't have a direct measure of it
- E.g., consider the causal DAG
  - A retailer does market research, expecting *Price* to influence *Sales* in a predictable way
  - A retailer sets the *Price* of a new product based on market research
  - The retailer can observe and measure *Behavior*, e.g.,
    - Discounts
    - Promotional campaign
  - There are unobserved vars that influence the model, e.g.,
    - Social media buzz
    - Word-of-mouth recommendation



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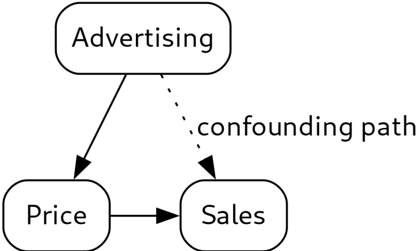
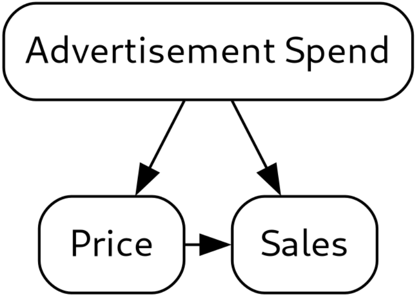
Front-door Paths in Causal Inference

- A front-door path reveals causal influence through an observable mediator
  - The causal effect flows: $A \to P \to S$
- Requirements for identifiability:
  - All confounders of $A \to P$ and $P \to S$ are observed and controlled
  - There are no back-door paths from A to S through unobserved variables
- Enables causal estimation when back-door adjustment is infeasible
- Example:
  - Advertising impacts sales through customer perception of price
  - A: Advertising, P: Price perception, S: Sales
- Pearl's front-door criterion provides a formal method for adjustment
  - Estimate $P(P|A)$, $P(S|P, A)$, and $P(A)$ from data to compute causal effect



Back-Door Paths

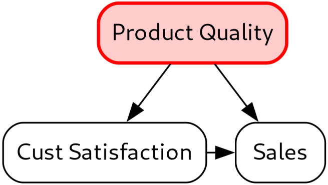
- A company wants to understand the causal effect of price on sales



- `Price` $\rightarrow$ `Sales` is the front-door path
- A confounder is `Advertising spend` since it can affect both:
  - The price the company can set (e.g., the cost increases to cover advertisement costs and the product is perceived as more valuable)
  - The sales (directly)
- The back-door path goes from `Sales` to `Price` via `Advertising spend`

Frontdoor and Backdoor Paths

- Question: *Will increasing our customer satisfaction increase our sales?*
  - Assume that the Causal DAG is



  - **Front-door path** (i.e., a direct causal relationship): *CustomerSatisfaction* $\to$ *Sales*
  - **Backdoor path**: *ProductQuality* is a common cause (confounder) of both *CustomerSatisfaction* and *Sales*
  - To analyze the relationship between customer satisfaction and sales, we need to:
    - Control for *ProductQuality* to close the backdoor path
    - Eliminate the confounding effect
  - In reality there are more confounding effects (e.g., price)

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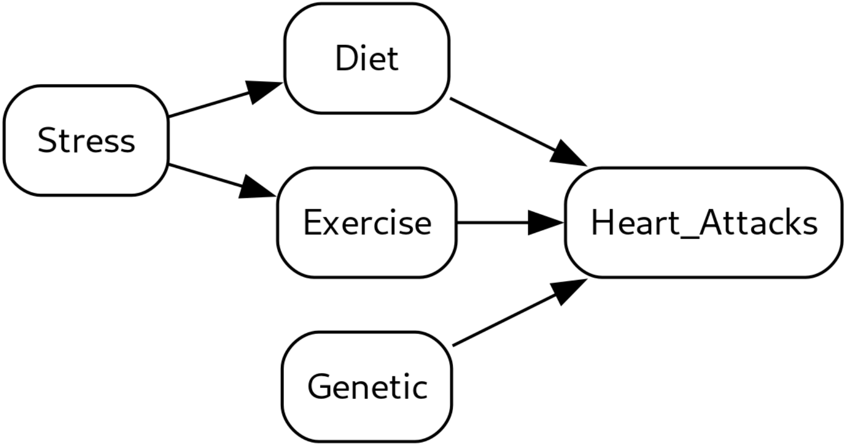
Building a DAG

- **Causal models** visually represent complex environments and relationships
- Nodes are like "nouns" in the model:
  - E.g., "price", "sales", "revenue", "birth weight", "gestation period"
  - Variables can be endogenous/exogenous and observed/unobserved
  - Complex relationships between variables:
    - Parents, children (direct relationships)
    - Descendants, ancestors (along the path)
    - Neighbors
- **Iterative Refinement**:
  - Models are continuously updated with new variables and insights
- **Modeling as a Communication Tool**:
  - A shared language that bridges gaps between technical and non-technical team members
- **Unobservable Variables**:
  - Supports inclusion of variables not empirically observed but known to exist
  - E.g., trust or competitor activity can be modeled despite lack of direct data

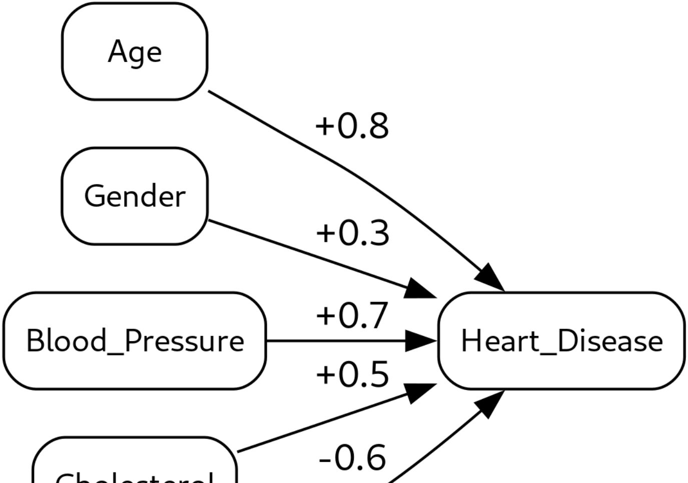
Heart Attack: Example

- What's the relationship between stress and heart attacks?
  - Stress is the treatment
  - Heart attack is the outcome
  - Stress is not a direct cause of heart attack
    - E.g., a stressed person tend to have poor eating habits



Weights

- Weights can be assigned to paths to represent the strength of the causal relationship
  - Weights can be estimated using statistical methods
- Sign represents the direction



Counterfactuals

- A **counterfactual** describes what would have happened under a different scenario
  - *"What would the outcome have been if X had been different?"*
  - *"If kangaroos had no tails, they would topple over"*
  - *"What if we had two suppliers of our product, rather than one? Would we have more sales?"*
  - *"Would customers be more satisfied if we could ship products in one week, rather than three weeks?"*
- **Causal reasoning**:
  - Goes beyond correlation and association
  - Requires a causal model (like an SCM) to simulate alternate realities
  - E.g.,
    - Actual: A student received tutoring and scored 85%
    - Counterfactual: What if the student didn't receive tutoring?
    - Causal model estimates the alternative outcome (e.g., 70%)
- **Challenges**:
  - Requires strong assumptions and accurate models
  - Difficult to validate directly since counterfactuals are unobservable