Bayesian Networks and Inference

Bayesian Networks

Today:

- Bayesian Networks
- How do we perform exact inference on Bayesian Networks?
- How do we reason about independence in Bayesian Networks?

Review

Joint

$P(X, Y, Z)$

$P(X=1, Y=0, Z=2)$

Conditional

$P(X|Y)$ ← Distribution-valued function of Y

$P(X=1 \mid Y=2)$

Marginal Distribution

$P(X)$ $P(Y)$

Independence

$P(X,Y) = P(X)P(Y)$

$X \perp Y$ $P(X) = P(X|Y)$

Conditional Indep

$P(X,Y|Z) = P(X|Z)\,P(Y|Z)$

$X \perp Y \mid Z$

$P(X|Z) = P(X|Y,Z)$

Bayesian Network

Binary Random Variables X_1, X_2, X_3

How many independent parameters to specify joint distribution?

2^3

X_1	X_2	X_3	$P(X_1, X_2, X_3)$
0	0	0	.
0	0	1	.
0	1	1	.
	⋮		⋮

Full Story: "Causality: Models, Reasoning and Inference" by Judea Pearl

Bayesian Network

Binary Random Variables X_1, X_2, X_3

How many independent parameters to specify joint distribution? 7

Bayesian Network

Binary Random Variables X_1, X_2, X_3

How many independent parameters to specify joint distribution? 7

For n binary R.V.s, $2^n - 1$ independent parameters specify the joint distribution.

Bayesian Network

Binary Random Variables X_1, X_2, X_3

How many independent parameters to specify joint distribution? 7

For n binary R.V.s, $2^n - 1$ independent parameters specify the joint distribution.

In general

$$\prod_{i=1}^{n} |\mathrm{support}(X_i)| - 1$$

Full Story: "Causality: Models, Reasoning and Inference" by Judea Pearl

Bayesian Network

Binary Random Variables X_1, X_2, X_3

How many independent parameters to specify joint distribution? 7

For n binary R.V.s, $2^n - 1$ independent parameters specify the joint distribution.

In general

$$\prod_{i=1}^{n} |\text{support}(X_i)| - 1$$

Bayesian Network: Directed Acyclic Graph (DAG) that represents a **joint probability distribution**

Full Story: "Causality: Models, Reasoning and Inference" by Judea Pearl

Bayesian Network

Binary Random Variables X_1, X_2, X_3

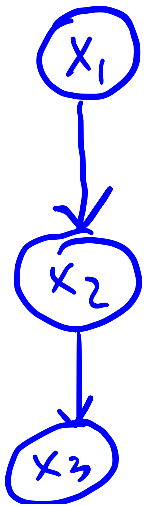
How many independent parameters to specify joint distribution? 7

For n binary R.V.s, $2^n - 1$ independent parameters specify the joint distribution.

In general

$$\prod_{i=1}^{n} |\text{support}(X_i)| - 1$$

Bayesian Network: Directed Acyclic Graph (DAG) that represents a **joint probability distribution**



Bayesian Network

Binary Random Variables X_1, X_2, X_3

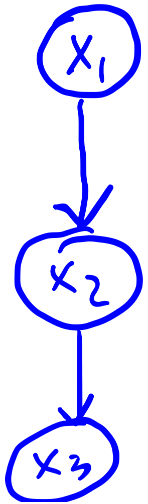
How many independent parameters to specify joint distribution? 7

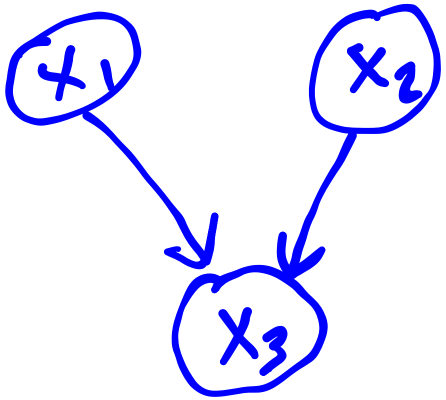
For n binary R.V.s, $2^n - 1$ independent parameters specify the joint distribution.

In general

$$\prod_{i=1}^{n} |\mathrm{support}(X_i)| - 1$$

Bayesian Network: Directed Acyclic Graph (DAG) that represents a **joint probability distribution**





Bayesian Network

Binary Random Variables X_1, X_2, X_3

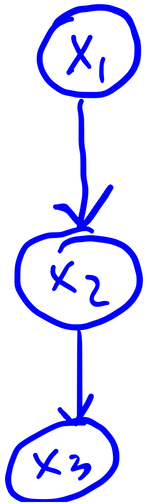
How many independent parameters to specify joint distribution? 7

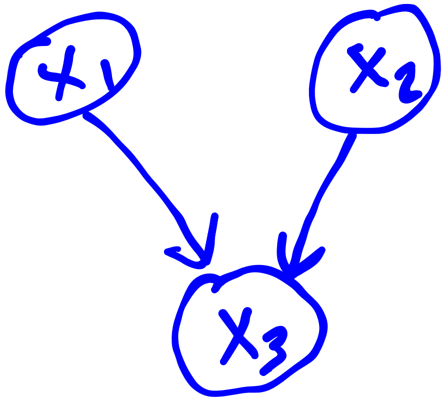
For n binary R.V.s, $2^n - 1$ independent parameters specify the joint distribution.

In general

$$\prod_{i=1}^{n} |\text{support}(X_i)| - 1$$

Bayesian Network: Directed Acyclic Graph (DAG) that represents a **joint probability distribution**





- Node:
- Edges encode:

Bayesian Network

Binary Random Variables X_1, X_2, X_3

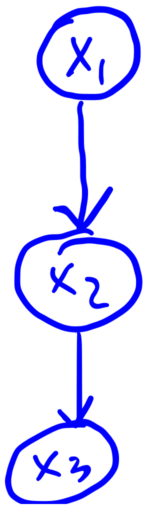
How many independent parameters to specify joint distribution? 7

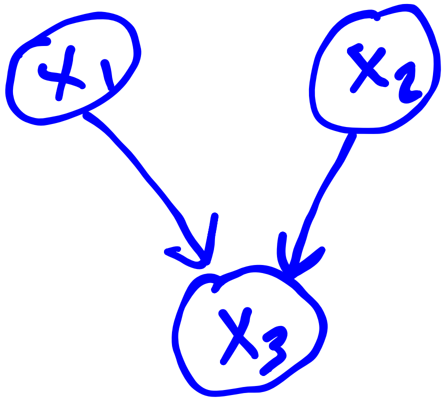
For n binary R.V.s, $2^n - 1$ independent parameters specify the joint distribution.

In general

$$\prod_{i=1}^{n} |\mathrm{support}(X_i)| - 1$$

Bayesian Network: Directed Acyclic Graph (DAG) that represents a **joint probability distribution**





- Node: Random Variable
- Edges encode:

Bayesian Network

Binary Random Variables X_1, X_2, X_3

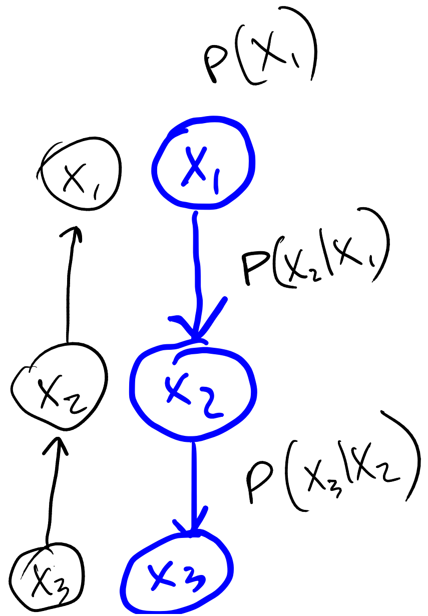
How many independent parameters to specify joint distribution? 7

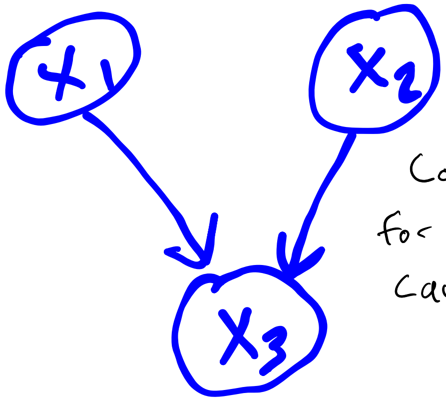
For n binary R.V.s, $2^n - 1$ independent parameters specify the joint distribution.

In general

$$\prod_{i=1}^{n} |\text{support}(X_i)| - 1$$

Bayesian Network: Directed Acyclic Graph (DAG) that represents a **joint probability distribution**





Correct BN for X_1 and X_2 causally influence X_3

- Node: Random Variable
- Edges encode:

Chain Rule

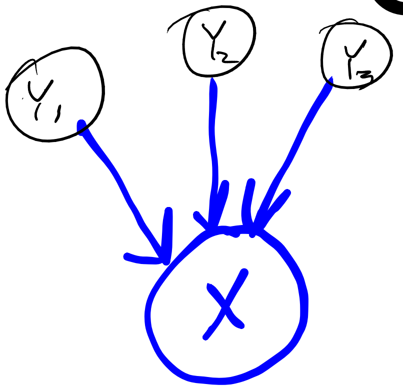
$$P(X_{1:n}) = \prod_{i=1}^{n} P(X_i \mid \text{pa}(X_i))$$

Joint parents

Counting Parameters

$Y \in \{0,1\}$

$X \in \{0,1\}$



For discrete R.V.s:

$$\rightarrow \quad \dim(\theta_X) = (|\text{support}(X)| - 1) \underline{\prod_{Y \in Pa(X)} |\text{support}(Y)|}$$

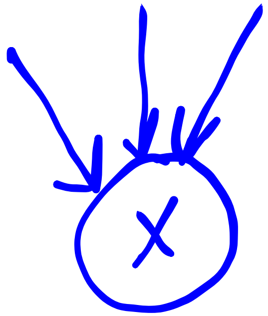
$P(X \mid Y_1, Y_2, Y_3)$

$\quad\quad\quad 1 \quad 1 \quad 1$

$\rightarrow P(X=0 \mid Y_1=1, Y_2=1, Y_3=1)$ 1 parameter

$P(X=1 \mid \ldots\ldots)$

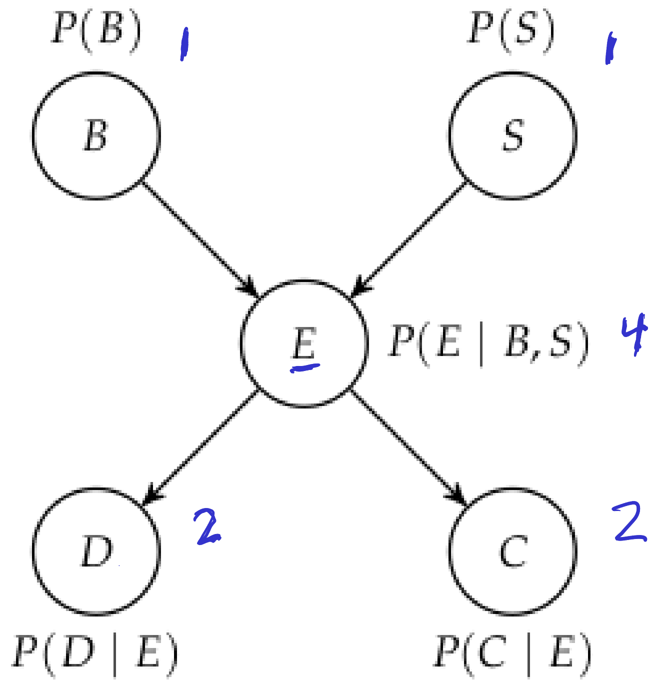
Counting Parameters



For discrete R.V.s:

$$\dim(\theta_X) = \underline{(|\text{support}(X)| - 1)} \underline{\prod_{Y \in Pa(X)} |\text{support}(Y)|}$$

All Binary



Naive independent params $2^5 - 1 = 31$

BN independent params $= 1+1+4+2+2 = 10$

Inference

Inputs

Outputs

Inference

Inputs

- Bayesian network structure

Outputs

Inference

Inputs

- Bayesian network structure
- Bayesian network parameters

Outputs

Inference

Inputs

- Bayesian network structure
- Bayesian network parameters
- Values of *evidence variables*

Outputs

Inference

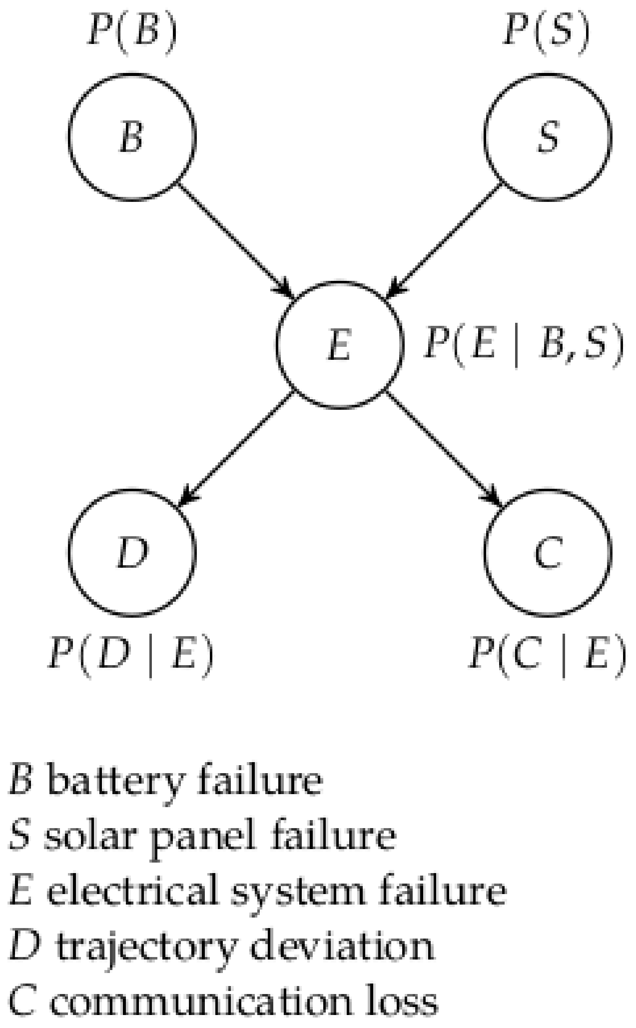
Inputs

- Bayesian network structure
- Bayesian network parameters
- Values of *evidence variables*

Outputs

- Posterior distribution of *query variables*

Inference



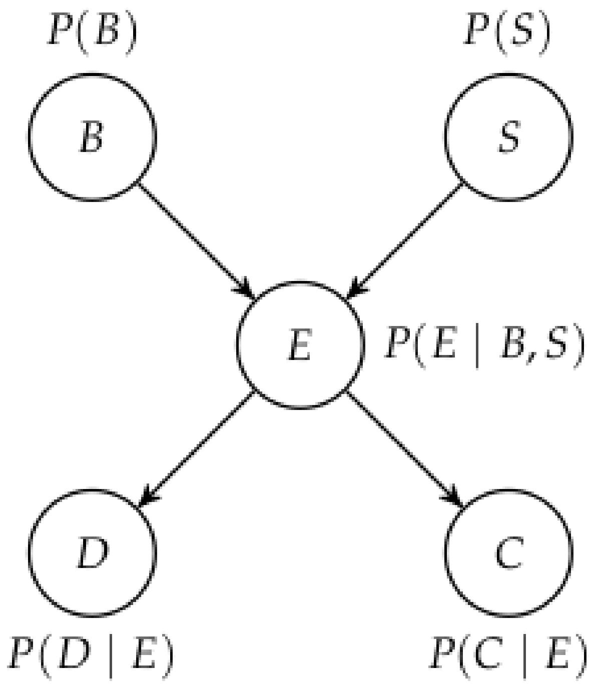
Inputs

- Bayesian network structure
- Bayesian network parameters
- Values of *evidence variables*

Outputs

- Posterior distribution of *query variables*

Inference



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

Inputs

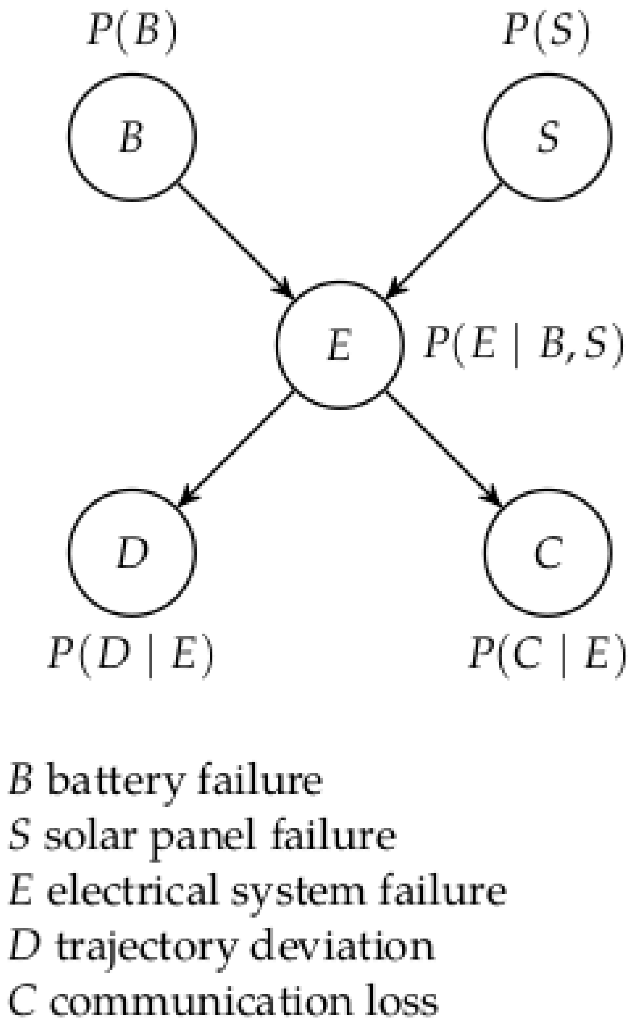
- Bayesian network structure
- Bayesian network parameters
- Values of *evidence variables*

Outputs

- Posterior distribution of *query variables*

Given that you have detected a trajectory deviation, and the battery has not failed what is the probability of a solar panel failure?

Inference



Inputs

- Bayesian network structure
- Bayesian network parameters
- Values of *evidence variables*

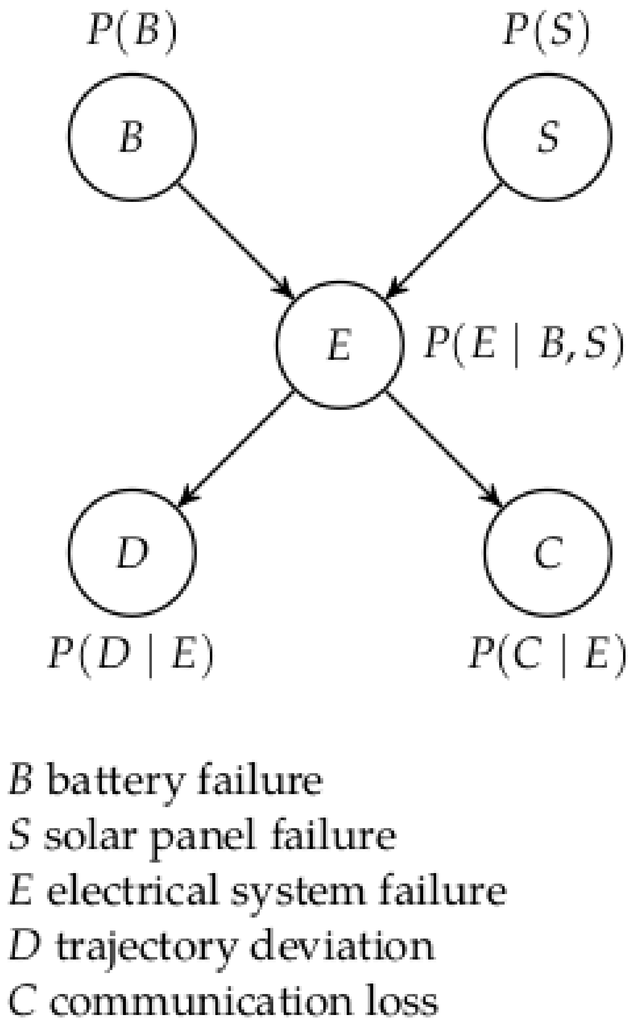
Outputs

- Posterior distribution of *query variables*

Given that you have detected a trajectory deviation, and the battery has not failed what is the probability of a solar panel failure?

$$P(S = 1 \mid D = 1, B = 0)$$

Inference



Inputs

- Bayesian network structure
- Bayesian network parameters
- Values of *evidence variables*

Outputs

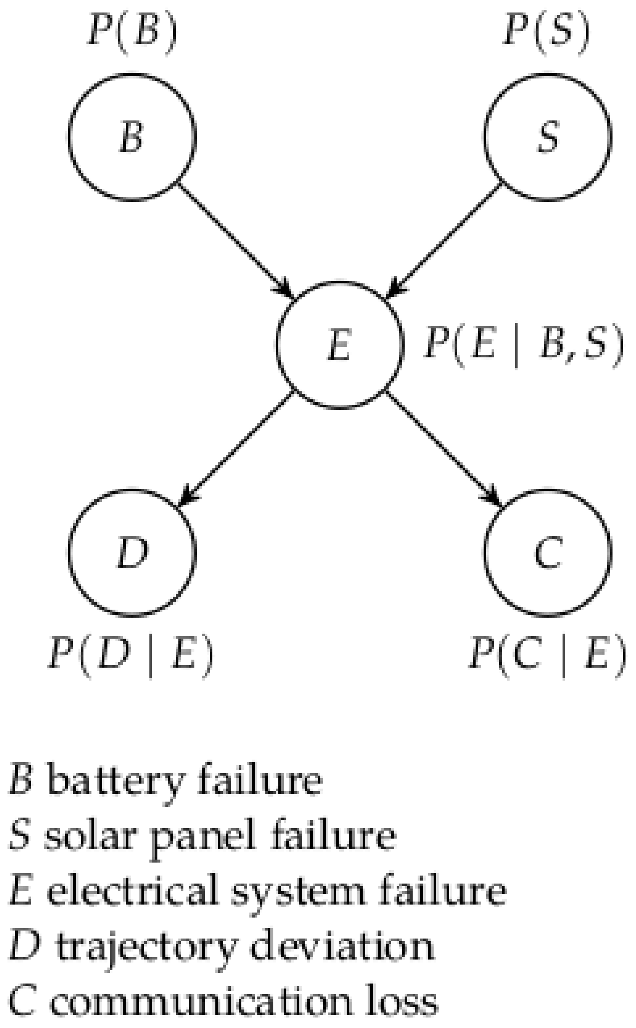
- Posterior distribution of *query variables*

Given that you have detected a trajectory deviation, and the battery has not failed what is the probability of a solar panel failure?

$$P(S = 1 \mid D = 1, B = 0)$$

Exact

Inference



Inputs

- Bayesian network structure
- Bayesian network parameters
- Values of *evidence variables*

Outputs

- Posterior distribution of *query variables*

Given that you have detected a trajectory deviation, and the battery has not failed what is the probability of a solar panel failure?

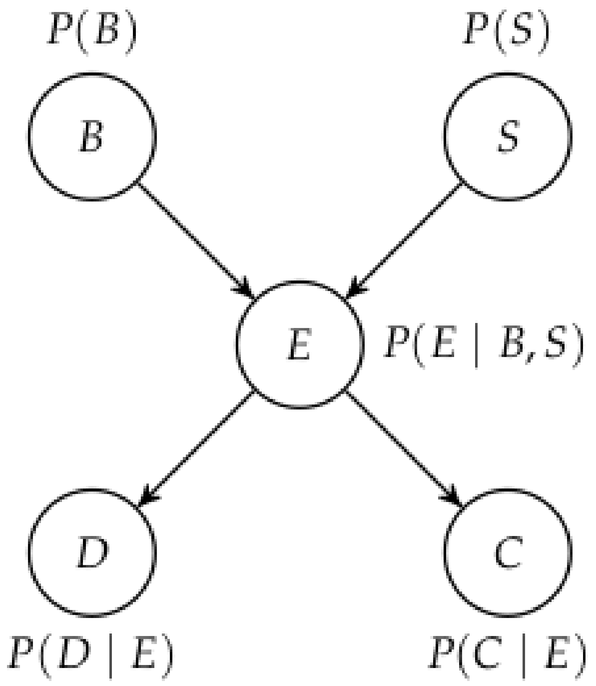
$$P(S = 1 \mid D = 1, B = 0)$$

Exact

Approximate

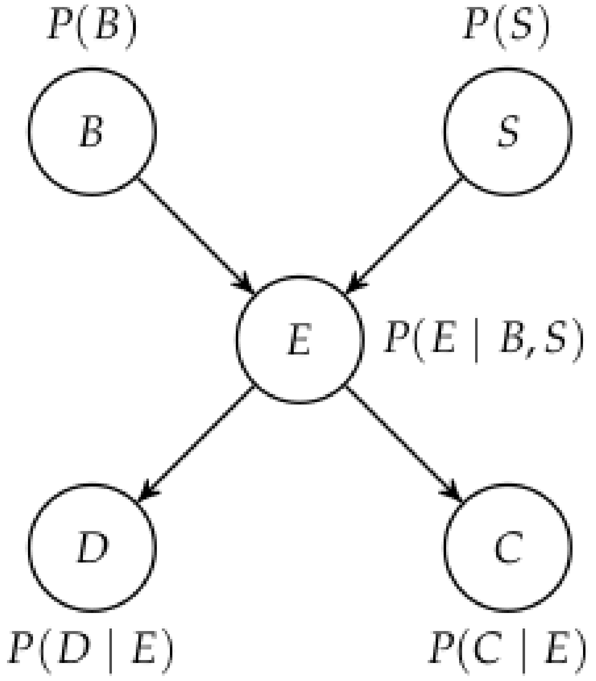
Exact Inference

Exact Inference



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

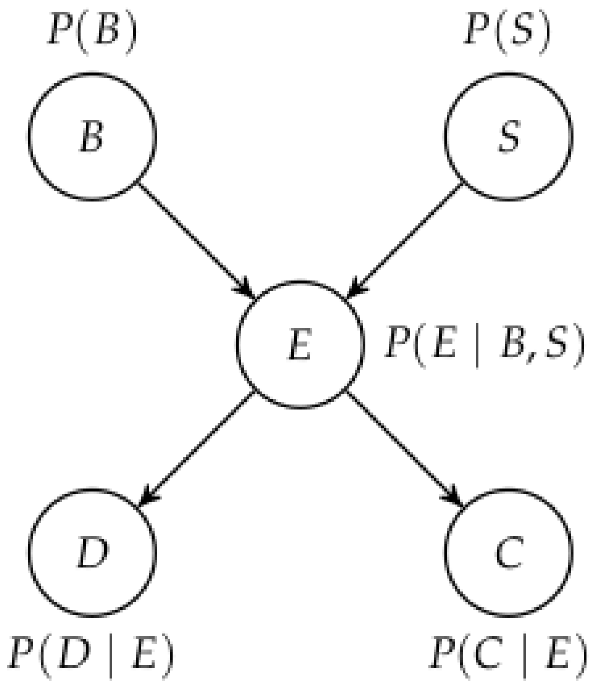
Exact Inference



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

$$P(S{=}1 \mid D{=}1, B{=}0)$$

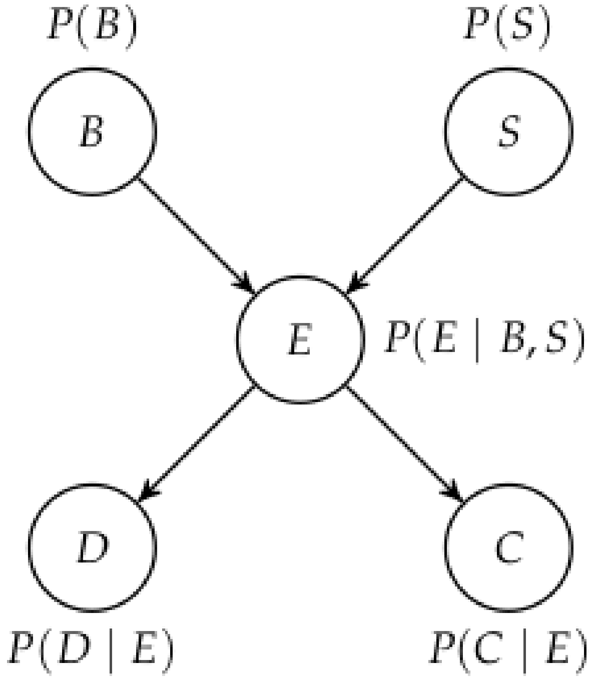
Exact Inference



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

$$P(S{=}1 \mid D{=}1, B{=}0) = \frac{P(S{=}1, D{=}1, B{=}0)}{P(D{=}1, B{=}0)}$$

Exact Inference

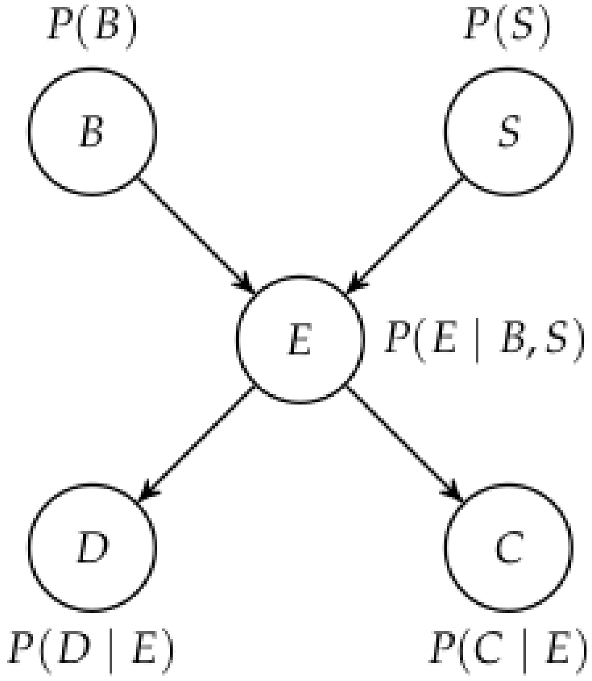


B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

$$P(S{=}1 \mid D{=}1, B{=}0) = \frac{P(S{=}1, D{=}1, B{=}0)}{P(D{=}1, B{=}0)}$$

$$P(S{=}1, D{=}1, B{=}0) = \sum_{e,c} P(B{=}0, S{=}1, E{=}e, D{=}1, C{=}c)$$

Exact Inference



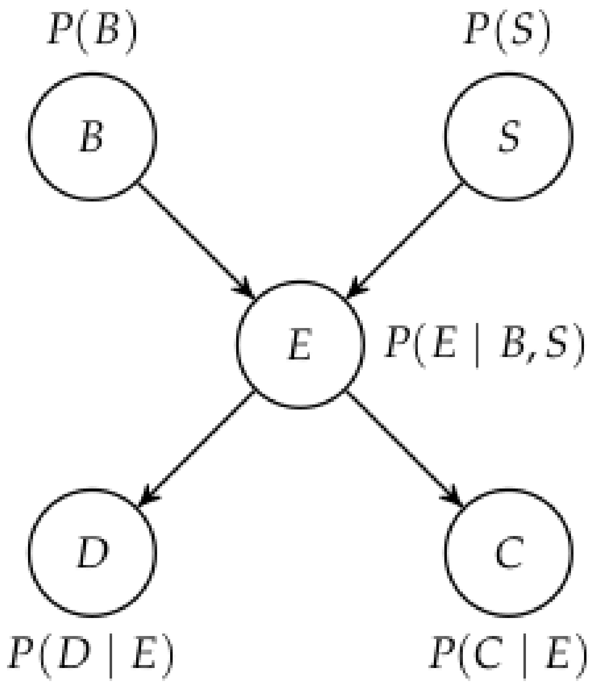
B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

$$P(S{=}1 \mid D{=}1, B{=}0) = \frac{P(S{=}1, D{=}1, B{=}0)}{P(D{=}1, B{=}0)}$$

$$P(S{=}1, D{=}1, B{=}0) = \sum_{e,c} P(B{=}0, S{=}1, E{=}e, D{=}1, C{=}c)$$

$$P(B{=}0, S{=}1, E, D{=}1, C)$$

Exact Inference



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

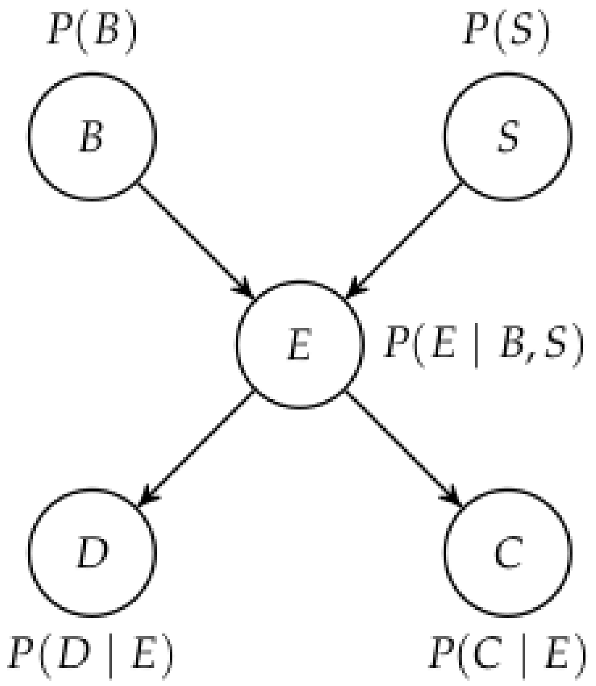
$$P(S{=}1 \mid D{=}1, B{=}0) = \frac{P(S{=}1, D{=}1, B{=}0)}{P(D{=}1, B{=}0)}$$

$$P(S{=}1, D{=}1, B{=}0) = \sum_{e,c} P(B{=}0, S{=}1, E{=}e, D{=}1, C{=}c)$$

$$P(B{=}0, S{=}1, E, D{=}1, C)$$
$$= P(B{=}0)\, P(S{=}1)\, P(E \mid B{=}0, S{=}1)\, P(D{=}1 \mid E)\, P(C{=}1 \mid E)$$

Bayesian Network Chain Rule

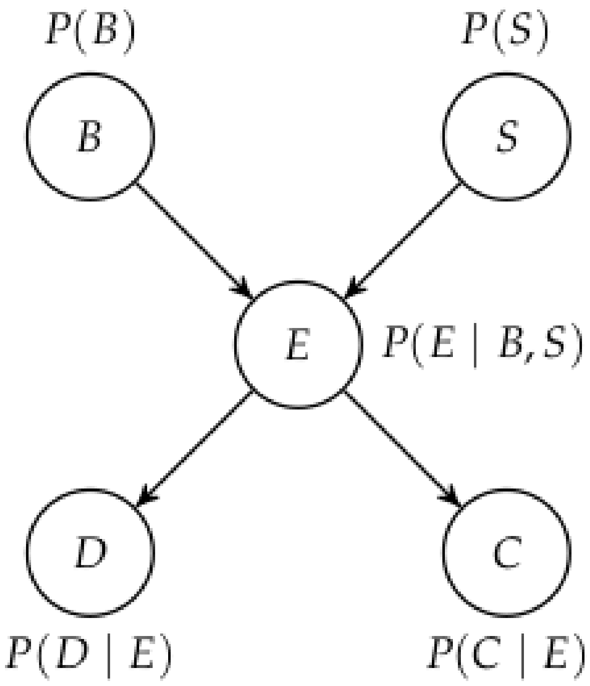
Exact Inference



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

Exact Inference

ϕ $\phi_3(X,Y,Z) = \phi_1(X,Y)\,\phi_2(Y,Z)$



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

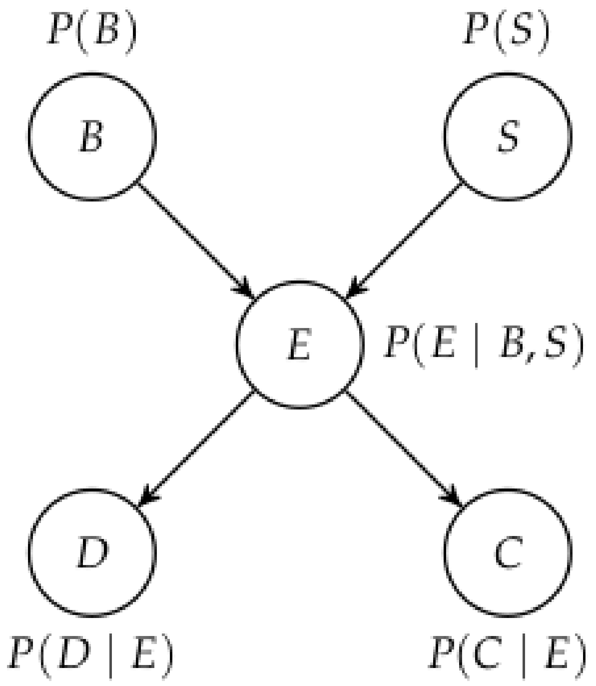
Product

X	Y	$\phi_1(X,Y)$
0	0	0.3
0	1	0.4
1	0	0.2
1	1	0.1

Y	Z	$\phi_2(Y,Z)$
0	0	0.2
0	1	0.0
1	0	0.3
1	1	0.5

X	Y	Z	$\phi_3(X,Y,Z)$
0	0	0	0.06
0	0	1	0.00
0	1	0	0.12
0	1	1	0.20
1	0	0	0.04
1	0	1	0.00
1	1	0	0.03
1	1	1	0.05

Exact Inference



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

Product

X	Y	$\phi_1(X, Y)$
0	0	0.3
0	1	0.4
1	0	0.2
1	1	0.1

Y	Z	$\phi_2(Y, Z)$
0	0	0.2
0	1	0.0
1	0	0.3
1	1	0.5

X	Y	Z	$\phi_3(X, Y, Z)$
0	0	0	0.06
0	0	1	0.00
0	1	0	0.12
0	1	1	0.20
1	0	0	0.04
1	0	1	0.00
1	1	0	0.03
1	1	1	0.05

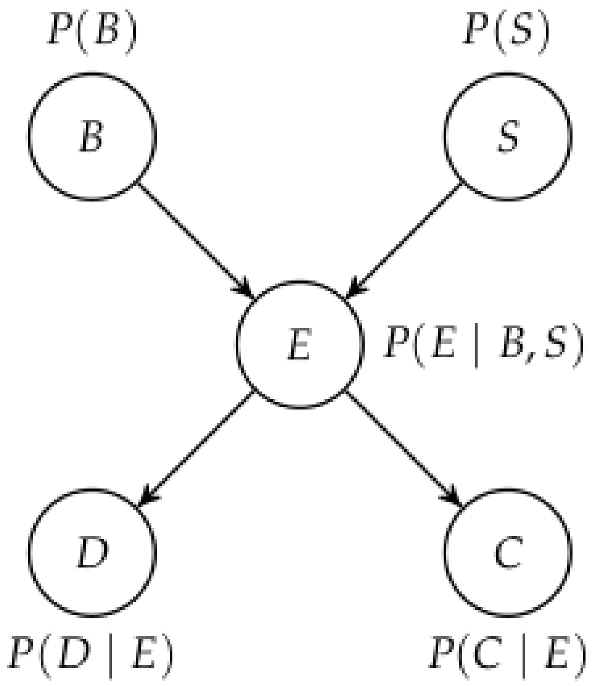
Condition

X	Y	Z	$\phi(X, Y, Z)$
0	0	0	0.08
0	0	1	0.31
0	1	0	0.09
0	1	1	0.37
1	0	0	0.01
1	0	1	0.05
1	1	0	0.02
1	1	1	0.07

$Y = 1$

X	Z	$\phi(X, Z)$
0	0	0.09
0	1	0.37
1	0	0.02
1	1	0.07

Exact Inference



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

Product

X	Y	$\phi_1(X,Y)$
0	0	0.3
0	1	0.4
1	0	0.2
1	1	0.1

Y	Z	$\phi_2(Y,Z)$
0	0	0.2
0	1	0.0
1	0	0.3
1	1	0.5

X	Y	Z	$\phi_3(X,Y,Z)$
0	0	0	0.06
0	0	1	0.00
0	1	0	0.12
0	1	1	0.20
1	0	0	0.04
1	0	1	0.00
1	1	0	0.03
1	1	1	0.05

Condition

X	Y	Z	$\phi(X,Y,Z)$
0	0	0	0.08
0	0	1	0.31
0	1	0	0.09
0	1	1	0.37
1	0	0	0.01
1	0	1	0.05
1	1	0	0.02
1	1	1	0.07

$Y = 1$

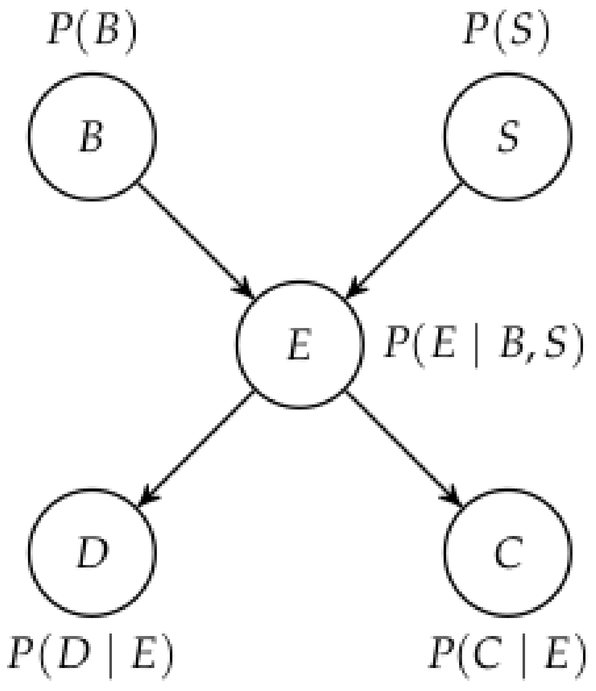
X	Z	$\phi(X,Z)$
0	0	0.09
0	1	0.37
1	0	0.02
1	1	0.07

Marginalize

X	Y	Z	$\phi(X,Y,Z)$
0	0	0	0.08
0	0	1	0.31
0	1	0	0.09
0	1	1	0.37
1	0	0	0.01
1	0	1	0.05
1	1	0	0.02
1	1	1	0.07

X	Z	$\phi(X,Z)$
0	0	0.17
0	1	0.68
1	0	0.03
1	1	0.12

Exact Inference



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

Product

X	Y	$\phi_1(X,Y)$
0	0	0.3
0	1	0.4
1	0	0.2
1	1	0.1

Y	Z	$\phi_2(Y,Z)$
0	0	0.2
0	1	0.0
1	0	0.3
1	1	0.5

X	Y	Z	$\phi_3(X,Y,Z)$
0	0	0	0.06
0	0	1	0.00
0	1	0	0.12
0	1	1	0.20
1	0	0	0.04
1	0	1	0.00
1	1	0	0.03
1	1	1	0.05

```
struct ExactInference end

function infer(M::ExactInference, bn, query, evidence)
    ϕ = prod(bn.factors)
    ϕ = condition(ϕ, evidence)
    for name in setdiff(variablenames(ϕ), query)
        ϕ = marginalize(ϕ, name)
    end
    return normalize!(ϕ)
end
```

Condition

X	Y	Z	$\phi(X,Y,Z)$
0	0	0	0.08
0	0	1	0.31
0	1	0	0.09
0	1	1	0.37
1	0	0	0.01
1	0	1	0.05
1	1	0	0.02
1	1	1	0.07

$Y = 1$

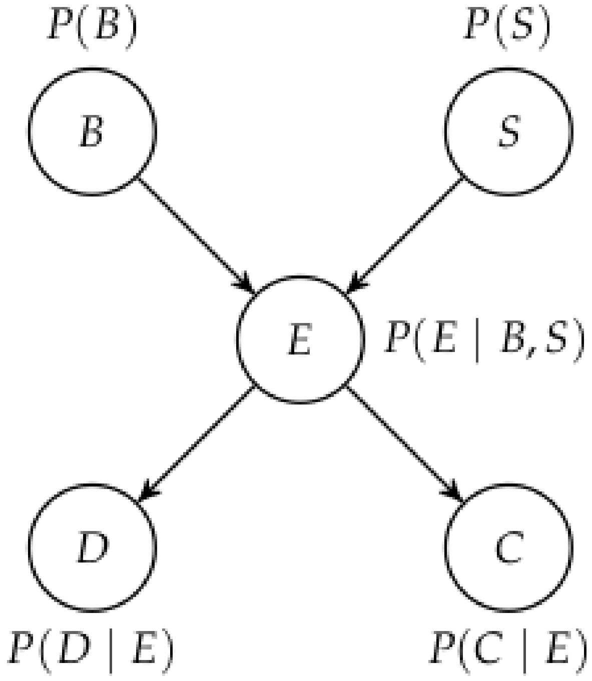
X	Z	$\phi(X,Z)$
0	0	0.09
0	1	0.37
1	0	0.02
1	1	0.07

Marginalize

X	Y	Z	$\phi(X,Y,Z)$
0	0	0	0.08
0	0	1	0.31
0	1	0	0.09
0	1	1	0.37
1	0	0	0.01
1	0	1	0.05
1	1	0	0.02
1	1	1	0.07

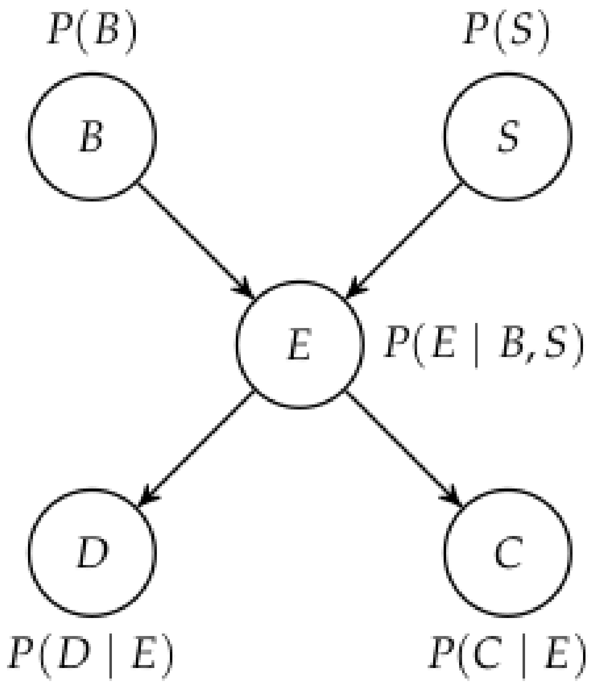
X	Z	$\phi(X,Z)$
0	0	0.17
0	1	0.68
1	0	0.03
1	1	0.12

Exact Inference: Variable Elimination



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

Exact Inference: Variable Elimination

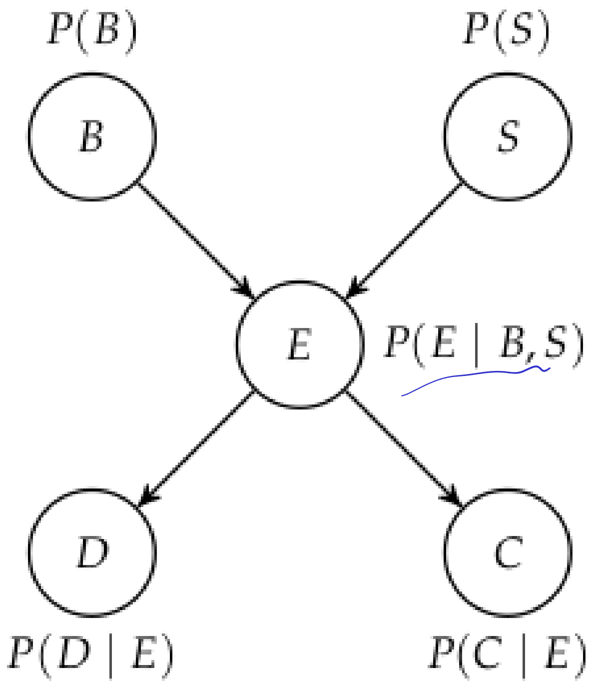


$P(B \mid d^1, c^1)$

$P(B \mid D=1, C=1)$

B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

Exact Inference: Variable Elimination



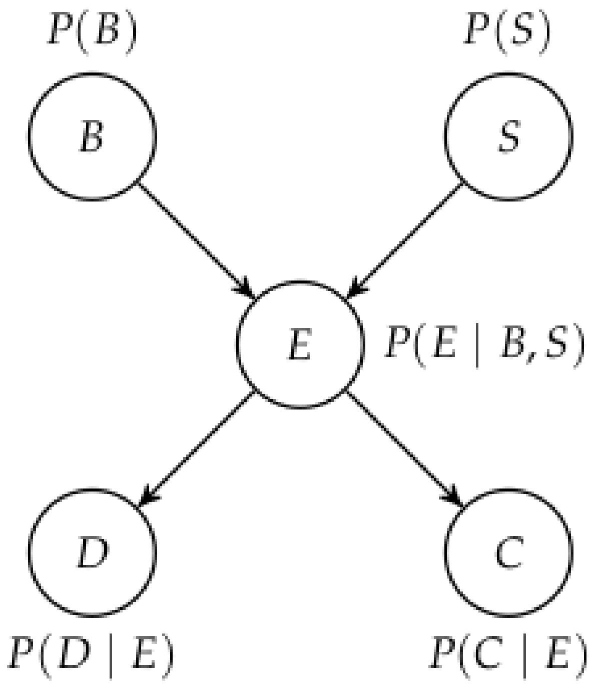
B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

$P(B \mid d^1, c^1)$

Start with

$\phi_1(B), \phi_2(S), \phi_3(E, B, S), \phi_4(D, E), \phi_5(C, E)$

Exact Inference: Variable Elimination



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

$P(B \mid d^1, c^1)$

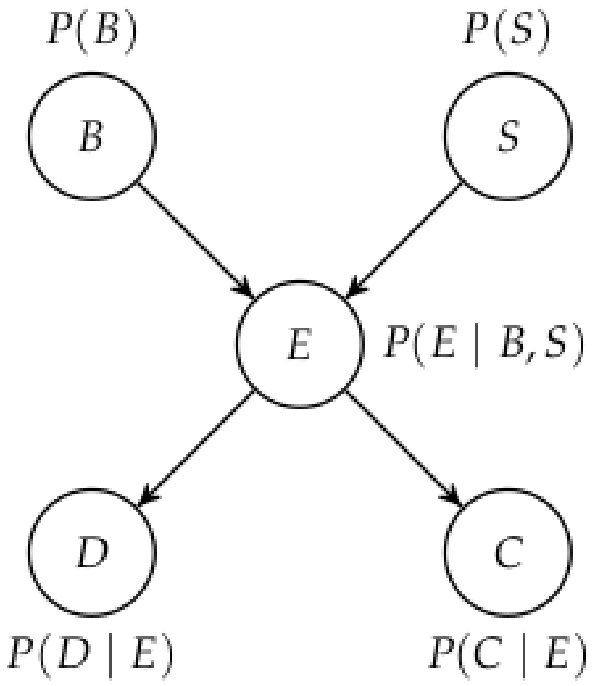
Start with

D=1 C=1

$\phi_1(B), \phi_2(S), \phi_3(E, B, S), \phi_4(D, E), \phi_5(C, E)$

Eliminate D and C (evidence) to get $\phi_6(E)$ and $\phi_7(E)$

Exact Inference: Variable Elimination



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

$P(B \mid d^1, c^1)$

Start with

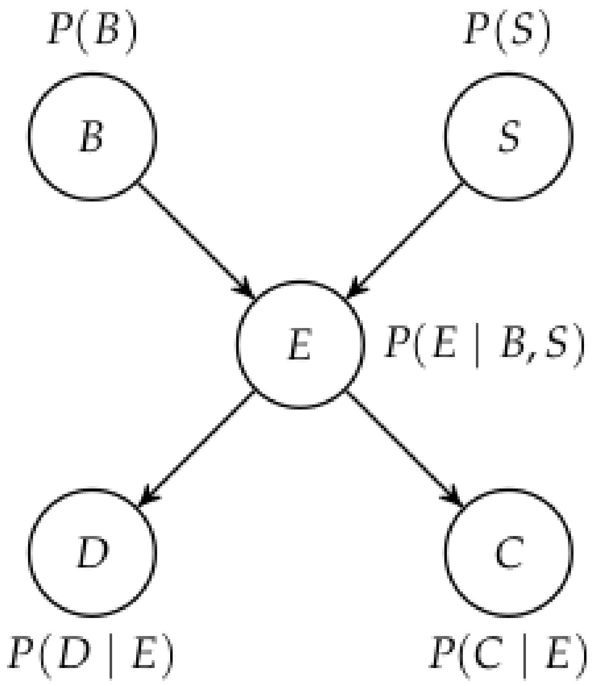
$\phi_1(B), \phi_2(S), \phi_3(E, B, S), \phi_4(D, E), \phi_5(C, E)$

Eliminate D and C (evidence) to get $\phi_6(E)$ and $\phi_7(E)$

Eliminate E

$$\phi_8(B, S) = \sum_e \phi_3(e, B, S)\phi_6(e)\phi_7(e)$$

Exact Inference: Variable Elimination



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

$P(B \mid d^1, c^1)$

Start with

$\phi_1(B), \phi_2(S), \phi_3(E,B,S), \phi_4(D,E), \phi_5(C,E)$

Eliminate D and C (evidence) to get $\phi_6(E)$ and $\phi_7(E)$

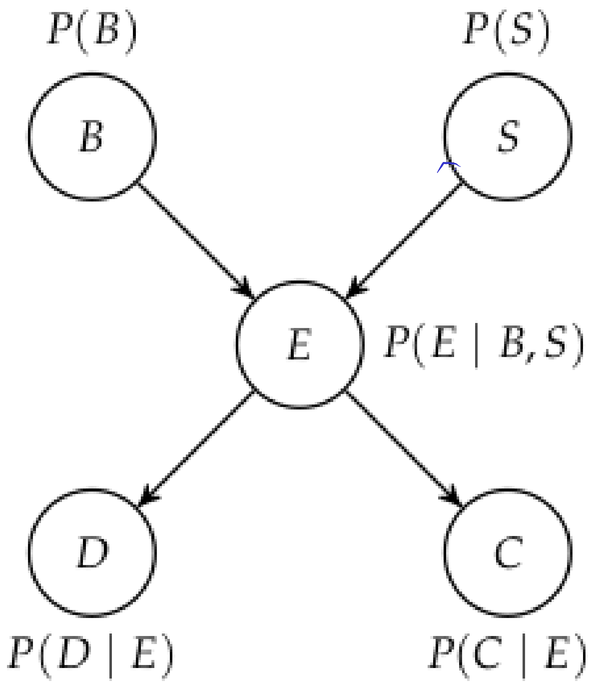
Eliminate E

$$\phi_8(B,S) = \sum_e \phi_3(e,B,S)\phi_6(e)\phi_7(e)$$

Eliminate S

$$\phi_9(B) = \sum_s \phi_2(s)\phi_8(B,s)$$

Exact Inference: Variable Elimination



$P(B \mid d^1, c^1)$

Start with

$\phi_1(B), \phi_2(S), \phi_3(E, B, S), \phi_4(D, E), \phi_5(C, E)$

Eliminate D and C (evidence) to get $\phi_6(E)$ and $\phi_7(E)$

Eliminate E

$$\phi_8(B, S) = \sum_e \phi_3(e, B, S)\phi_6(e)\phi_7(e)$$

Eliminate S

$$\phi_9(B) = \sum_s \phi_2(s)\phi_8(B, s)$$

B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

Elimination $\longrightarrow$

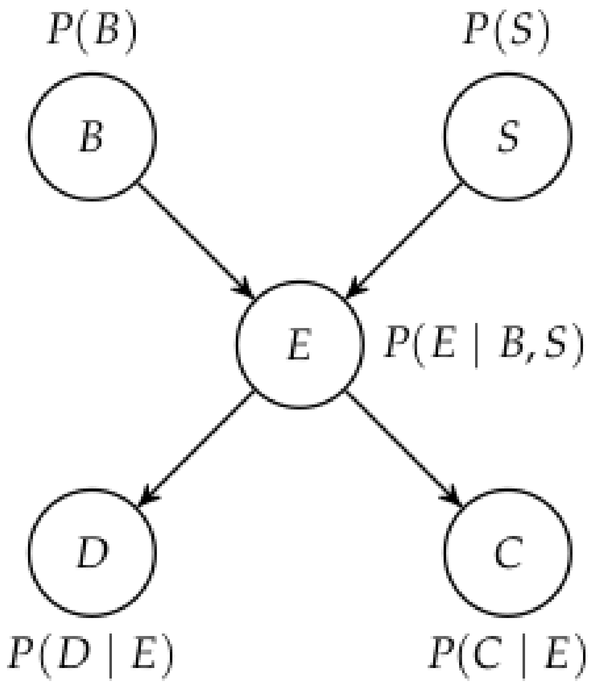
$$P(B \mid d^1, c^1) \propto \phi_1(B) \sum_s \left(\phi_2(s) \sum_e \left(\phi_3(e \mid B, s)\phi_4(d^1 \mid e)\phi_5(c^1 \mid e) \right) \right)$$

vs

Naive $\longrightarrow$

$$P(B \mid d^1, c^1) \propto \sum_s \sum_e \phi_1(B)\phi_2(s)\phi_3(e \mid B, s)\phi_4(d^1 \mid e)\phi_5(c^1 \mid e)$$

Exact Inference: Variable Elimination



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

$P(B \mid d^1, c^1)$

Start with

$\phi_1(B), \phi_2(S), \phi_3(E, B, S), \phi_4(D, E), \phi_5(C, E)$

Eliminate D and C (evidence) to get $\phi_6(E)$ and $\phi_7(E)$

Eliminate E

$$\phi_8(B, S) = \sum_e \phi_3(e, B, S)\phi_6(e)\phi_7(e)$$

Eliminate S

$$\phi_9(B) = \sum_s \phi_2(s)\phi_8(B, s)$$

$$P(B \mid d^1, c^1) \propto \phi_1(B) \sum_s \left(\phi_2(s) \sum_e \left(\phi_3(e \mid B, s)\phi_4(d^1 \mid e)\phi_5(c^1 \mid e) \right) \right)$$

vs

$$P(B \mid d^1, c^1) \propto \sum_s \sum_e \phi_1(B)\phi_2(s)\phi_3(e \mid B, s)\phi_4(d^1 \mid e)\phi_5(c^1 \mid e)$$

Choosing optimal order is NP-hard

Break

What does conditional independence mean?

https://kunalmenda.com/2019/02/21/causation-and-correlation/

What does conditional independence mean?

$X \perp Y \mid Z$

https://kunalmenda.com/2019/02/21/causation-and-correlation/

What does conditional independence mean?

$X \perp Y \mid Z \implies$

https://kunalmenda.com/2019/02/21/causation-and-correlation/

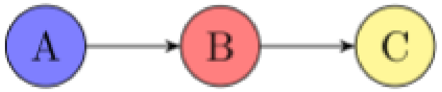
What does conditional independence mean?

$X \perp Y \mid Z \implies$ All of X's influence on Y comes through Z $\qquad P(X \mid Z) = P(X \mid Y, Z)$

https://kunalmenda.com/2019/02/21/causation-and-correlation/

What does conditional independence mean?

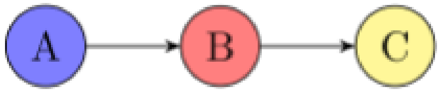
$X \perp Y \mid Z \implies$ All of X's influence on Y comes through Z $\qquad P(X \mid Z) = P(X \mid Y, Z)$



https://kunalmenda.com/2019/02/21/causation-and-correlation/

What does conditional independence mean?

$X \perp Y \mid Z \implies$ All of X's influence on Y comes through Z $\quad P(X \mid Z) = P(X \mid Y, Z)$

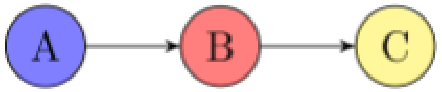


$A \perp C \mid B$?

https://kunalmenda.com/2019/02/21/causation-and-correlation/

What does conditional independence mean?

$X \perp Y \mid Z \implies$ All of X's influence on Y comes through Z $\quad P(X \mid Z) = P(X \mid Y, Z)$

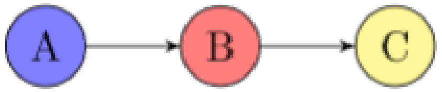


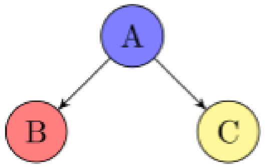
$A \perp C \mid B$? Yes

https://kunalmenda.com/2019/02/21/causation-and-correlation/

What does conditional independence mean?

$X \perp Y \mid Z \quad \Longrightarrow \quad$ All of X's influence on Y comes through Z $\qquad P(X \mid Z) = P(X \mid Y, Z)$



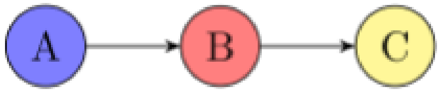


$A \perp C \mid B$? Yes

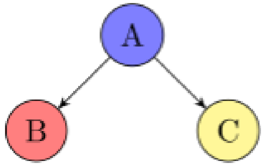
https://kunalmenda.com/2019/02/21/causation-and-correlation/

What does conditional independence mean?

$X \perp Y \mid Z \implies$ All of X's influence on Y comes through Z $\qquad P(X \mid Z) = P(X \mid Y, Z)$



$A \perp C \mid B$? Yes

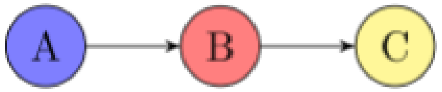


$B \perp C \mid A$?

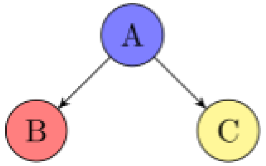
https://kunalmenda.com/2019/02/21/causation-and-correlation/

What does conditional independence mean?

$X \perp Y \mid Z \implies$ All of X's influence on Y comes through Z $\quad P(X \mid Z) = P(X \mid Y, Z)$



$A \perp C \mid B$? Yes

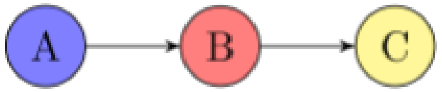


$B \perp C \mid A$? Yes

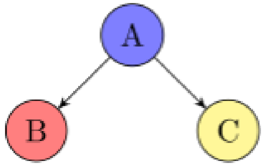
https://kunalmenda.com/2019/02/21/causation-and-correlation/

What does conditional independence mean?

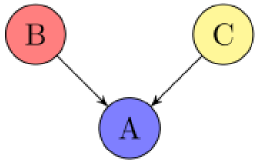
$X \perp Y \mid Z \implies$ All of X's influence on Y comes through Z $\quad P(X \mid Z) = P(X \mid Y, Z)$



$A \perp C \mid B$? Yes



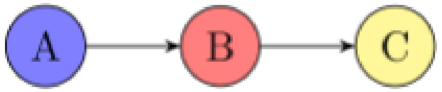
$B \perp C \mid A$? Yes



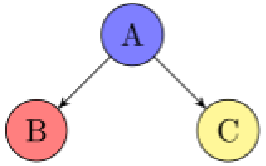
https://kunalmenda.com/2019/02/21/causation-and-correlation/

What does conditional independence mean?

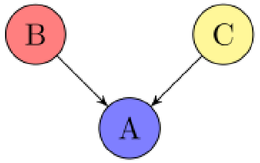
$X \perp Y \mid Z \implies$ All of X's influence on Y comes through Z $\qquad P(X \mid Z) = P(X \mid Y, Z)$



$A \perp C \mid B$? Yes



$B \perp C \mid A$? Yes

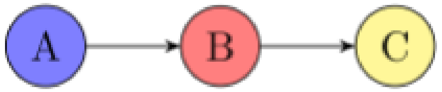


$B \perp C \mid A$?

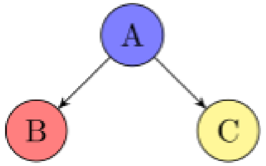
https://kunalmenda.com/2019/02/21/causation-and-correlation/

What does conditional independence mean?

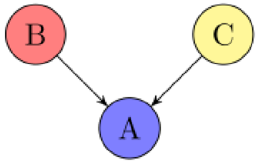
$X \perp Y \mid Z \implies$ All of X's influence on Y comes through Z $\quad P(X \mid Z) = P(X \mid Y, Z)$



$A \perp C \mid B$? Yes



$B \perp C \mid A$? Yes

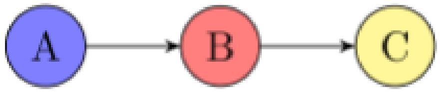


$B \perp C \mid A$? Inconclusive

https://kunalmenda.com/2019/02/21/causation-and-correlation/

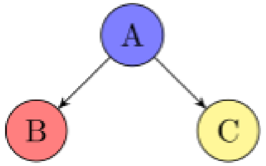
What does conditional independence mean?

$X \perp Y \mid Z \implies$ All of X's influence on Y comes through Z $\quad P(X \mid Z) = P(X \mid Y, Z)$

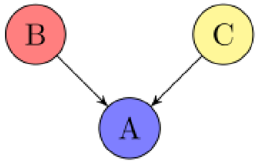


$A \perp C \mid B$? Yes

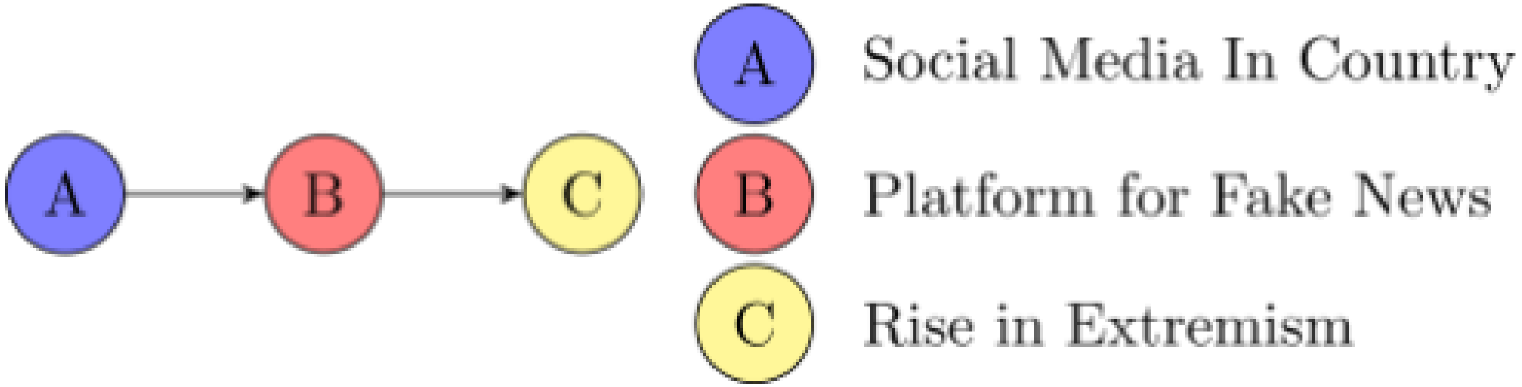
Mediator



$B \perp C \mid A$? Yes



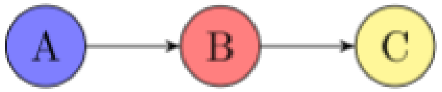
$B \perp C \mid A$? Inconclusive



https://kunalmenda.com/2019/02/21/causation-and-correlation/

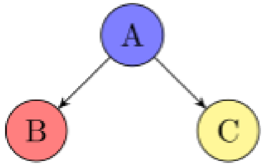
What does conditional independence mean?

$X \perp Y \mid Z \implies$ All of X's influence on Y comes through Z $\quad P(X \mid Z) = P(X \mid Y, Z)$



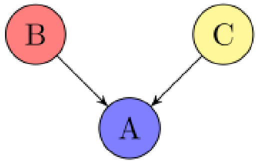
$A \perp C \mid B$? Yes

Mediator

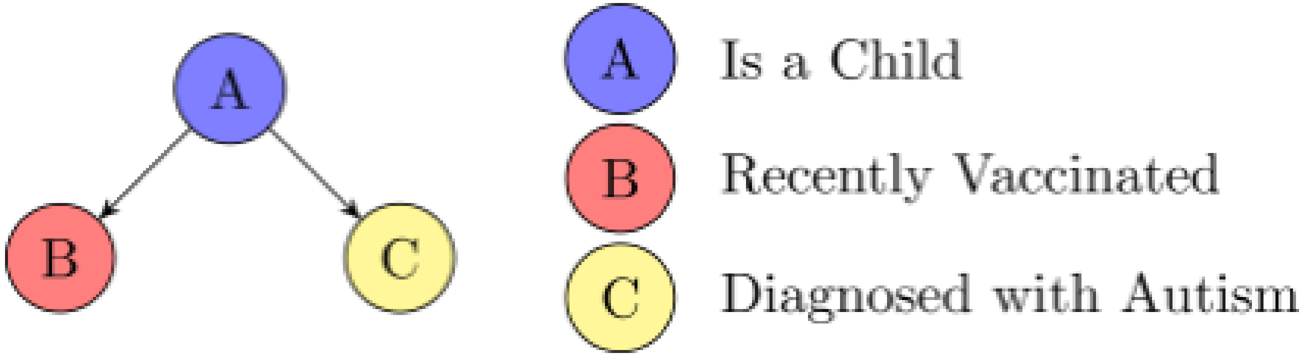


$B \perp C \mid A$? Yes

Confounder



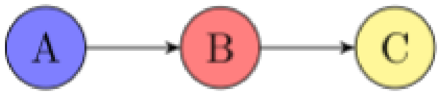
$B \perp C \mid A$? Inconclusive



https://kunalmenda.com/2019/02/21/causation-and-correlation/

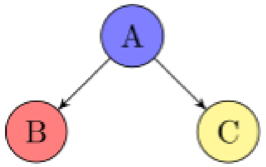
What does conditional independence mean?

$X \perp Y \mid Z \implies$ All of X's influence on Y comes through Z $\quad P(X \mid Z) = P(X \mid Y, Z)$



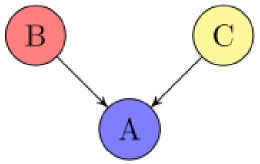
$A \perp C \mid B$? Yes

Mediator



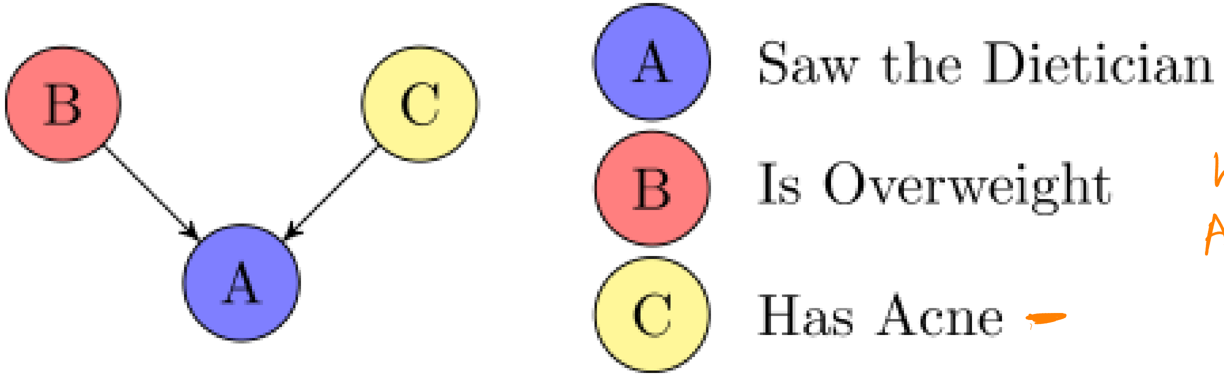
$B \perp C \mid A$? Yes

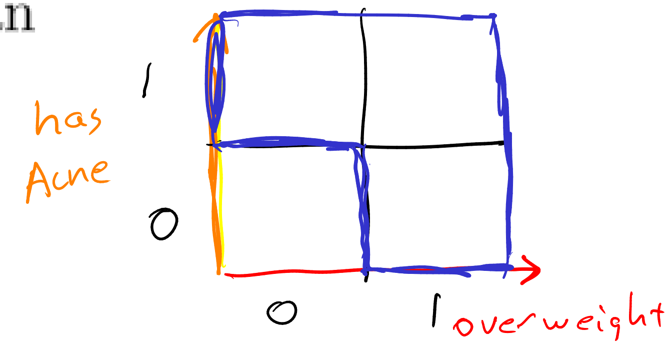
Confounder



$B \perp C \mid A$? Inconclusive

Collider

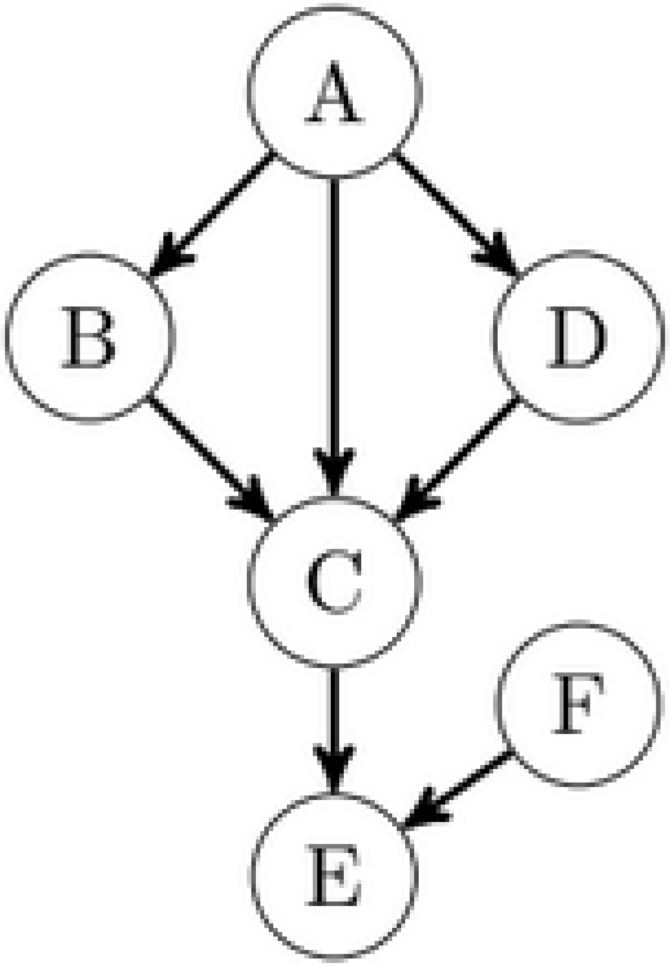




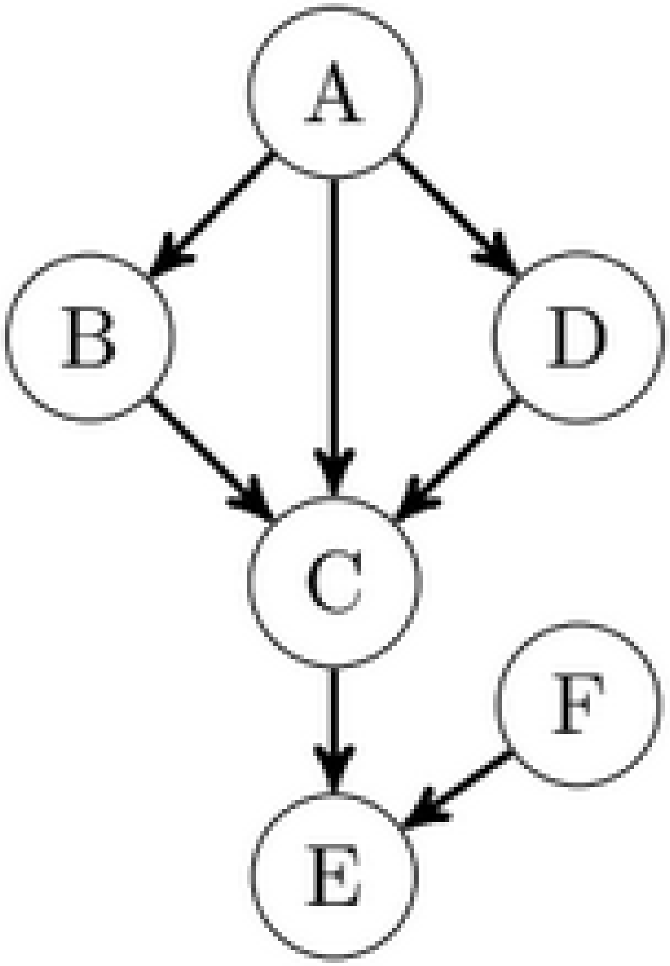
https://kunalmenda.com/2019/02/21/causation-and-correlation/

More Complex Example

More Complex Example

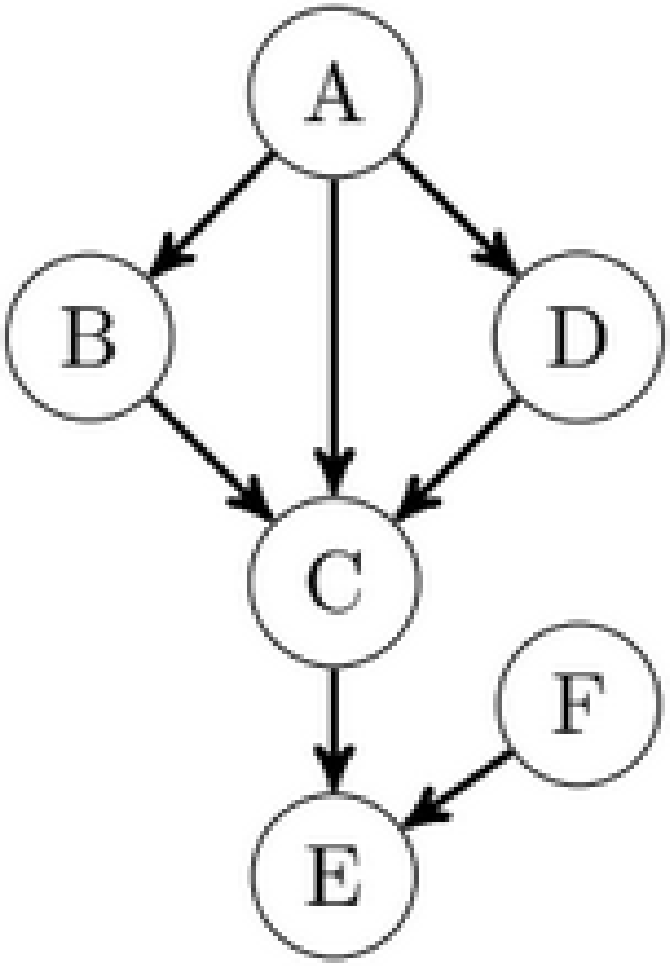


More Complex Example



$(B \perp D \mid A)$?

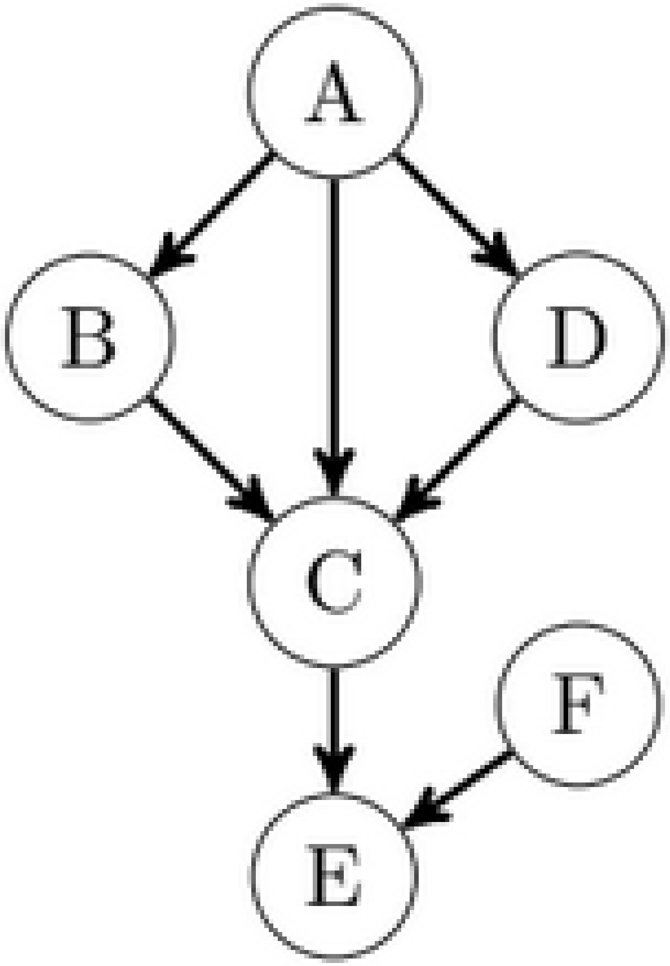
More Complex Example



$(B \perp D \mid A)$?

Yes!

More Complex Example

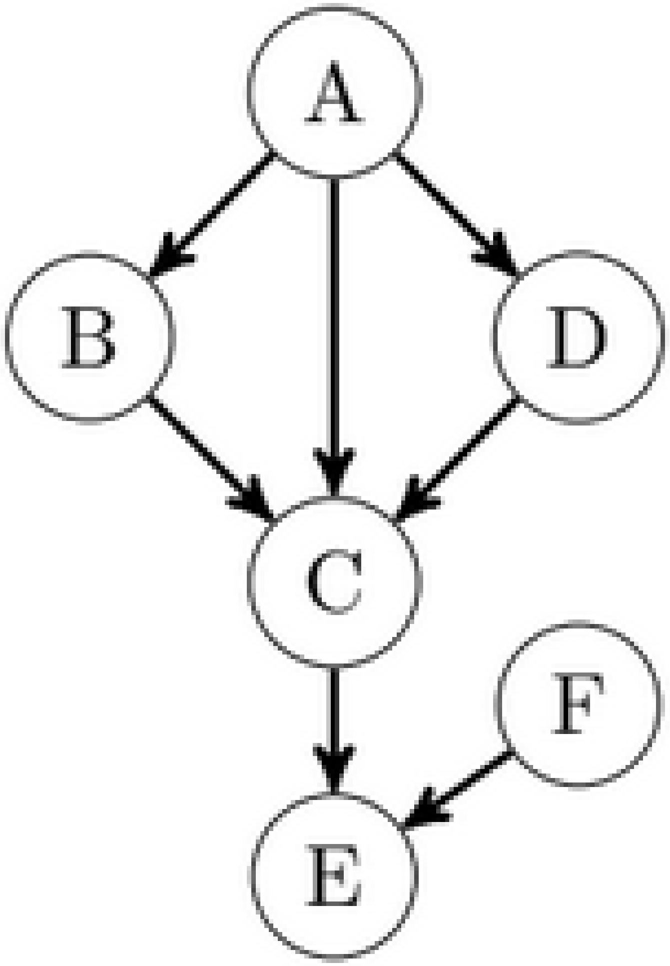


$(B \perp D \mid A)$?

Yes!

$(B \perp D \mid E)$?

More Complex Example



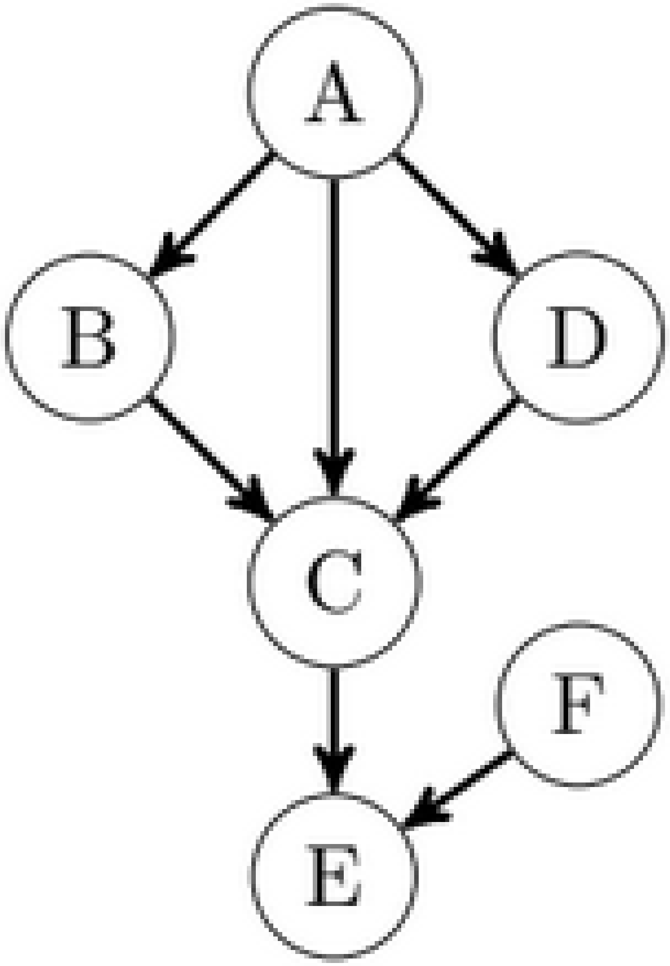
$(B \perp D \mid A)$?

Yes!

$(B \perp D \mid E)$?

~~No~~ Inconclusive

More Complex Example



$(B \perp D \mid A)$?

Yes!

$(B \perp D \mid E)$?

No

Why is this relevant?

d-Separation

*short for "directionally separated"

d-Separation

Let $\mathcal{C}$ be a set of random variables.

*short for "directionally separated"

d-Separation

$\mathscr{C}$

Let $\mathcal{C}$ be a set of random variables.

A *path* between A and B is *d-separated** by $\mathcal{C}$ if any of the following are true

*short for "directionally separated"

d-Separation

Let $\mathcal{C}$ be a set of random variables.

A *path* between A and B is *d-separated** by $\mathcal{C}$ if any of the following are true

1. The path contains a *chain* $X \rightarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$

*short for "directionally separated"

d-Separation

Let $\mathcal{C}$ be a set of random variables.

A *path* between A and B is *d-separated** by $\mathcal{C}$ if any of the following are true

1. The path contains a *chain* $X \rightarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$

*short for "directionally separated"

d-Separation

Let $\mathcal{C}$ be a set of random variables.

A *path* between A and B is *d-separated** by $\mathcal{C}$ if any of the following are true

1. The path contains a *chain* $X \rightarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
3. The path contains an *inverted fork* (v-structure) $X \rightarrow Y \leftarrow Z$ such that Y is *not* in $\mathcal{C}$ and no descendant of Y is in $\mathcal{C}$.

$$\begin{tikzcd}
A \arrow[dr] & & B \arrow[dl] \\
& C \arrow[d] & \\
& D &
\end{tikzcd}$$

$\mathcal{C} = \{D\}$

path $A \rightarrow C \leftarrow B$

not d-separated

$A \perp B$

$\not\Rightarrow A \perp B | D$

*short for "directionally separated"

d-Separation

Let $\mathcal{C}$ be a set of random variables.

A *path* between A and B is *d-separated** by $\mathcal{C}$ if any of the following are true

1. The path contains a *chain* $X \to Y \to Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \to Z$ such that $Y \in \mathcal{C}$
3. The path contains an *inverted fork* (v-structure) $X \to Y \leftarrow Z$ such that Y is *not* in $\mathcal{C}$ and no descendant of Y is in $\mathcal{C}$.

We say that A and B are *d-separated* by $\mathcal{C}$ if all paths between A and B are d-separated by $\mathcal{C}$.

*short for "directionally separated"

d-Separation

Let $\mathcal{C}$ be a set of random variables.

A *path* between A and B is *d-separated** by $\mathcal{C}$ if any of the following are true

1. The path contains a *chain* $X \rightarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
3. The path contains an *inverted fork* (v-structure) $X \rightarrow Y \leftarrow Z$ such that Y is *not* in $\mathcal{C}$ and no descendant of Y is in $\mathcal{C}$.

We say that A and B are *d-separated* by $\mathcal{C}$ if all paths between A and B are d-separated by $\mathcal{C}$.

If A and B are d-separated by $\mathcal{C}$ then $A \perp B \mid \mathcal{C}$

*short for "directionally separated"

Proving Conditional Independence

1. The path contains a *chain* $X \to Y \to Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \to Z$ such that $Y \in \mathcal{C}$
3. The path contains an *inverted fork* (v-structure) $X \to Y \leftarrow Z$ such that $Y \notin \mathcal{C}$ and no descendant of Y is in $\mathcal{C}$.

Proving Conditional Independence

1. Enumerate all (non-cyclic) paths between nodes in question

1. The path contains a *chain* $X \to Y \to Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \to Z$ such that $Y \in \mathcal{C}$
3. The path contains an *inverted fork* (v-structure) $X \to Y \leftarrow Z$ such that $Y \notin \mathcal{C}$ and no descendant of Y is in $\mathcal{C}$.

Proving Conditional Independence

1. Enumerate all (non-cyclic) paths between nodes in question
2. Check all paths for d-separation

1. The path contains a *chain* $X \rightarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
3. The path contains an *inverted fork* (v-structure) $X \rightarrow Y \leftarrow Z$ such that $Y \notin \mathcal{C}$ and no descendant of Y is in $\mathcal{C}$.

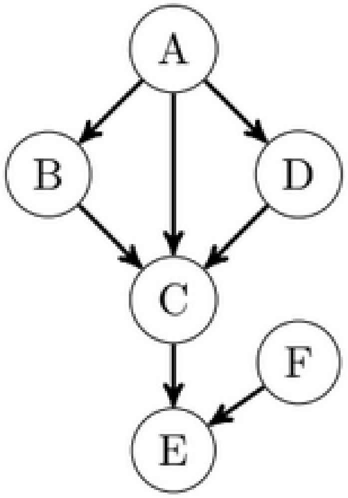
Proving Conditional Independence

1. Enumerate all (non-cyclic) paths between nodes in question
2. Check all paths for d-separation
3. If all paths d-separated, then CE

1. The path contains a *chain* $X \rightarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
3. The path contains an *inverted fork* (v-structure) $X \rightarrow Y \leftarrow Z$ such that $Y \notin \mathcal{C}$ and no descendant of Y is in $\mathcal{C}$.

Proving Conditional Independence

1. Enumerate all (non-cyclic) paths between nodes in question
2. Check all paths for d-separation
3. If all paths d-separated, then CE

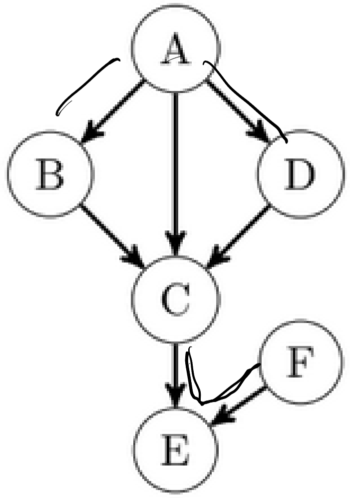


1. The path contains a *chain* $X \rightarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
3. The path contains an *inverted fork* (v-structure) $X \rightarrow Y \leftarrow Z$ such that $Y \notin \mathcal{C}$ and no descendant of Y is in $\mathcal{C}$.

Proving Conditional Independence

1. Enumerate all (non-cyclic) paths between nodes in question
2. Check all paths for d-separation
3. If all paths d-separated, then CE

conditional independence



$\mathcal{C} = \{C, E\}$

Example: $(B \perp D \mid \overbrace{C, E})$?

$B \leftarrow A \rightarrow D$ rule 2 not d-sep $\longrightarrow$ inconclusive

$B \rightarrow C \leftarrow D$ rule 2 not d-sep

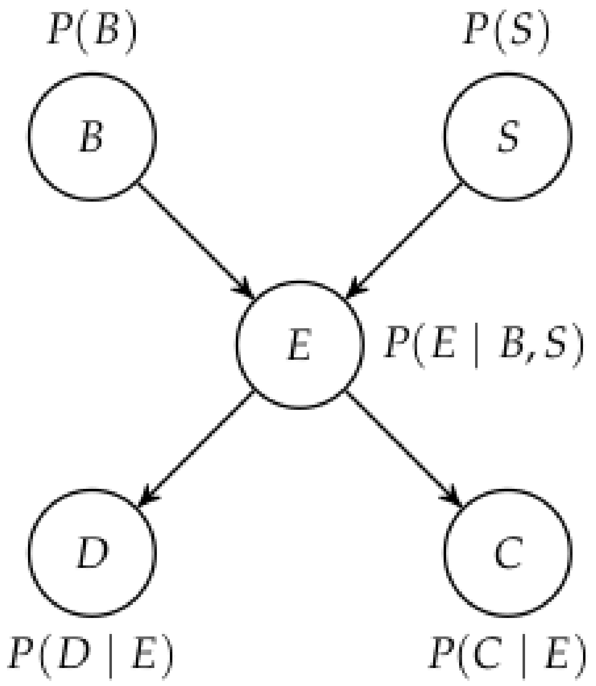
$B \leftarrow A \rightarrow C \leftarrow D$ rule 2 not d-sep
rule 3 not d-sep

$B \rightarrow C \leftarrow A \rightarrow D$ rule 2 not d-sep
rule 3 not d-sep

1. The path contains a *chain* $X \rightarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
3. The path contains an *inverted fork* (v-structure) $X \rightarrow Y \leftarrow Z$ such that $Y \notin \mathcal{C}$ and no descendant of Y is in $\mathcal{C}$.

Exercise

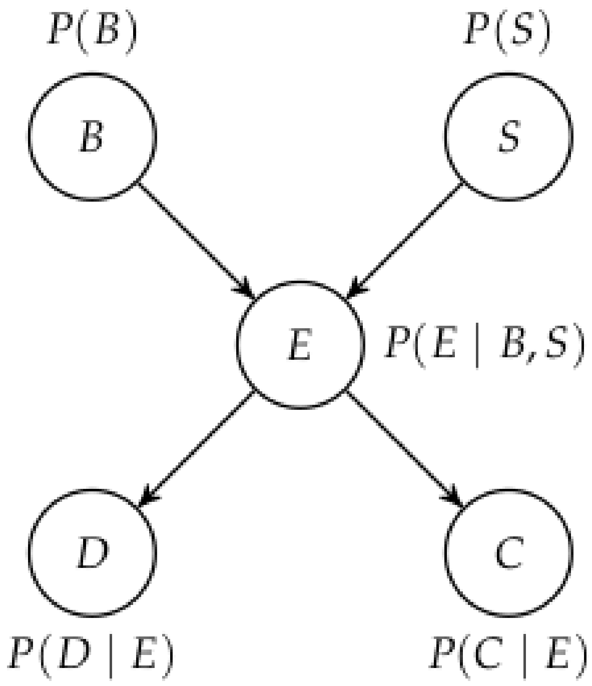
1. The path contains a *chain* $X \rightarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
3. The path contains an *inverted fork* (v-structure) $X \rightarrow Y \leftarrow Z$ such that $Y \notin \mathcal{C}$ and no descendant of Y is in $\mathcal{C}$.



Exercise

B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

1. The path contains a *chain* $X \rightarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
3. The path contains an *inverted fork* (v-structure) $X \rightarrow Y \leftarrow Z$ such that $Y \notin \mathcal{C}$ and no descendant of Y is in $\mathcal{C}$.



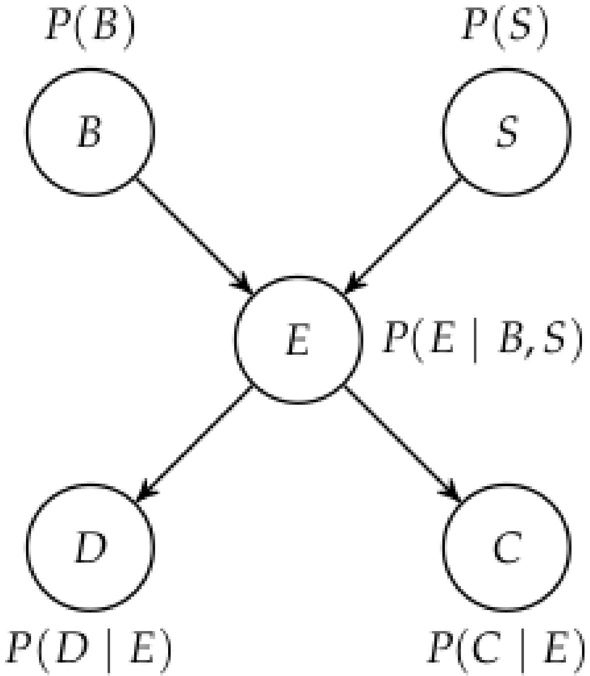
B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

Exercise

$$D \perp C \mid B\,?$$

1. The path contains a *chain* $X \to Y \to Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \to Z$ such that $Y \in \mathcal{C}$
3. The path contains an *inverted fork* (v-structure) $X \to Y \leftarrow Z$ such that $Y \notin \mathcal{C}$ and no descendant of Y is in $\mathcal{C}$.

Exercise



B battery failure
S solar panel failure
E electrical system failure
D trajectory deviation
C communication loss

$$D \perp C \mid B\ ?$$

$$D \perp C \mid E\ ?$$

1. The path contains a *chain* $X \rightarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
2. The path contains a *fork* $X \leftarrow Y \rightarrow Z$ such that $Y \in \mathcal{C}$
3. The path contains an *inverted fork* (v-structure) $X \rightarrow Y \leftarrow Z$ such that $Y \notin \mathcal{C}$ and no descendant of Y is in $\mathcal{C}$.

Recap