



Review: probability

Random variables: sunshine $S \in \{0, 1\}$, rain $R \in \{0, 1\}$

Joint distribution:

s	r	$\mathbb{P}(S = s, R = r)$
0	0	0.20
0	1	0.08
1	0	0.70
1	1	0.02

Marginal distribution:

s	$\mathbb{P}(S = s)$
0	0.28
1	0.72

(aggregate rows)



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(aggregate rows)

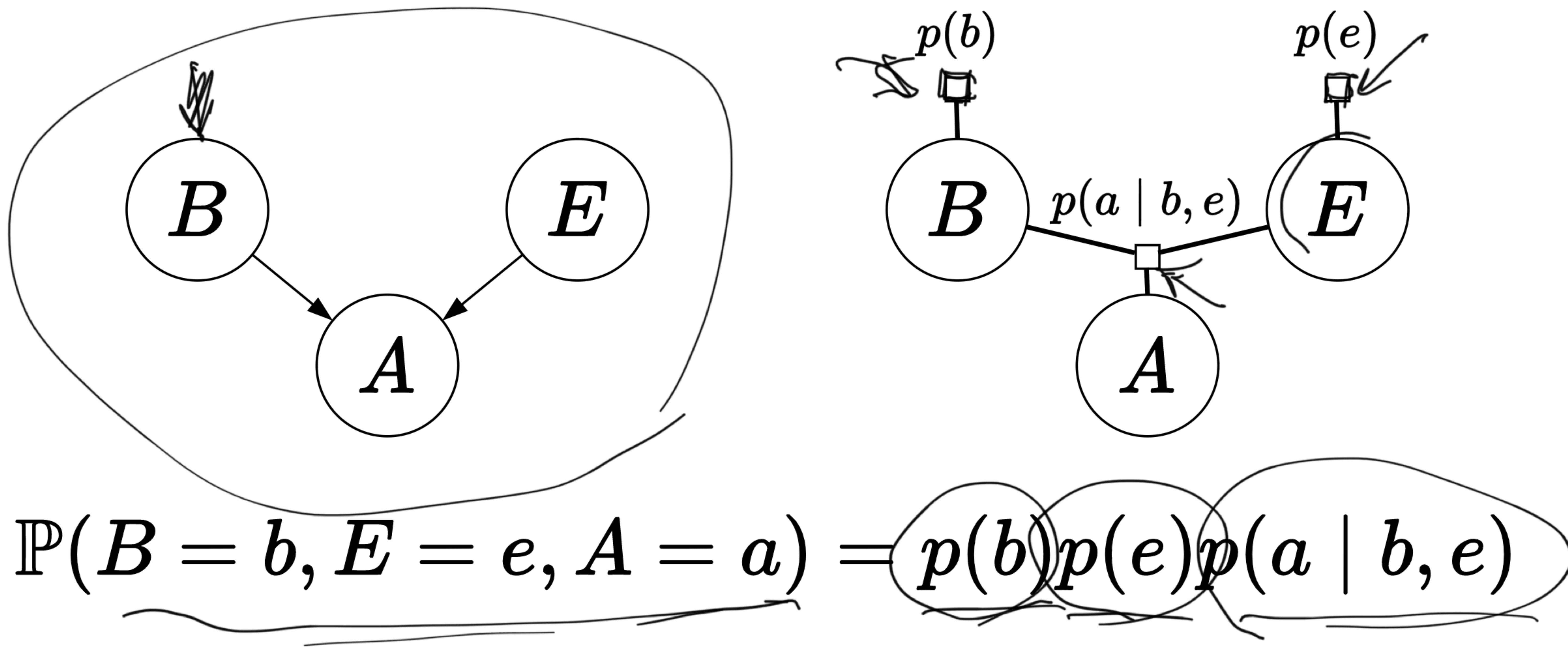
Conditional distribution:

s	$\mathbb{P}(S = s R = 1)$
0	0.8
1	0.2

(select rows, normalize)

divide
0.08 + 0.02
0.08 / 0.10

Bayesian network (alarm)

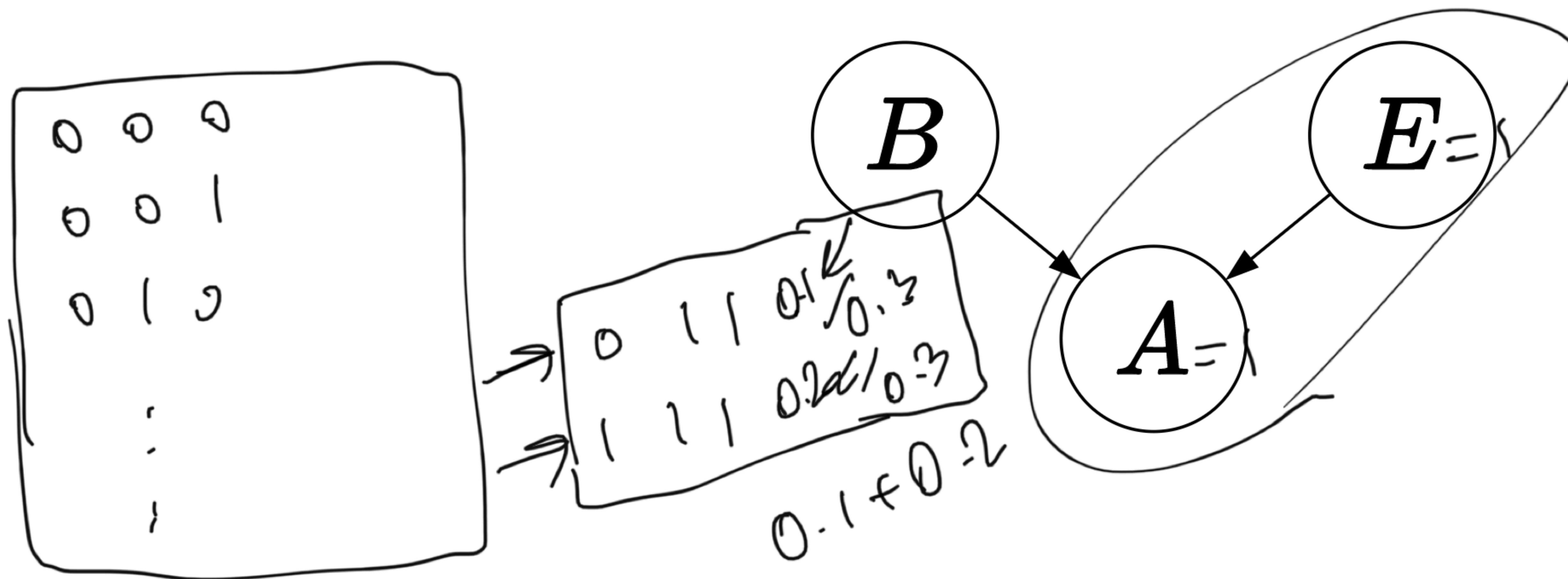


Bayesian networks are a special case of factor graphs!

probabilistic \equiv weight



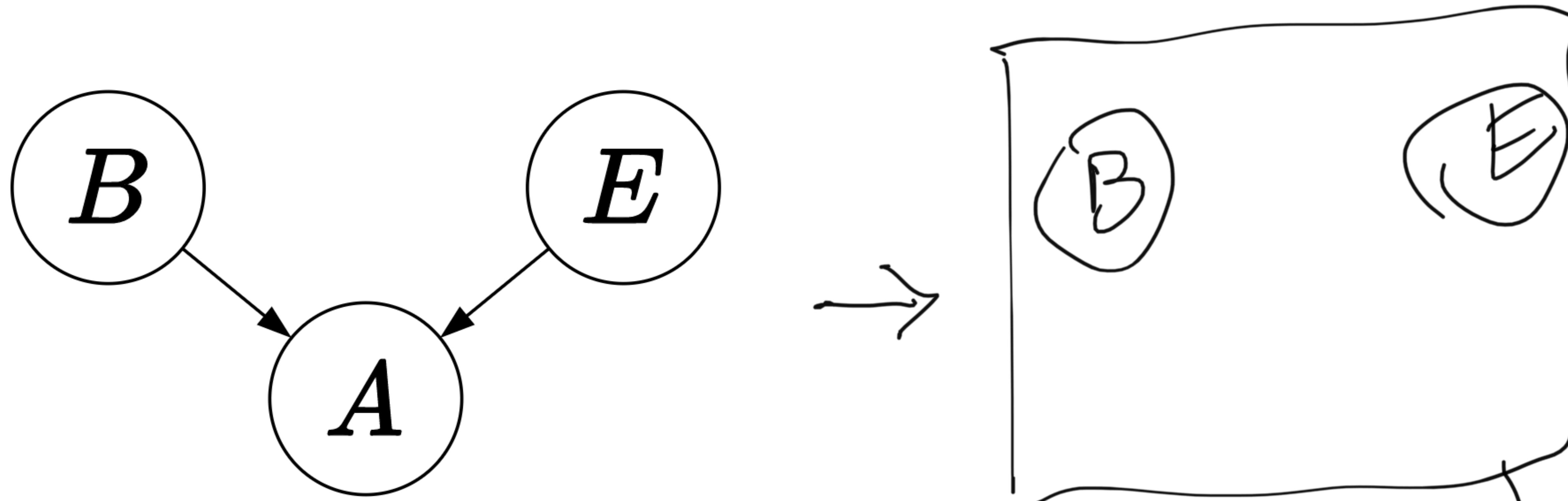
Explaining away



Key idea: explaining away

Suppose two causes positively influence an effect.
Conditioned on the effect, conditioning on one cause
reduces the probability of the other cause.

Consistency of sub-Bayesian networks



A short calculation:

$$\mathbb{P}(B = b, E = e) = \sum_a \mathbb{P}(B = b, E = e, A = a)$$

$$\stackrel{\text{def}}{=} \sum_a p(b)p(e)p(a \mid b, e)$$

$$= p(b)p(e) \sum_a p(a \mid b, e)$$

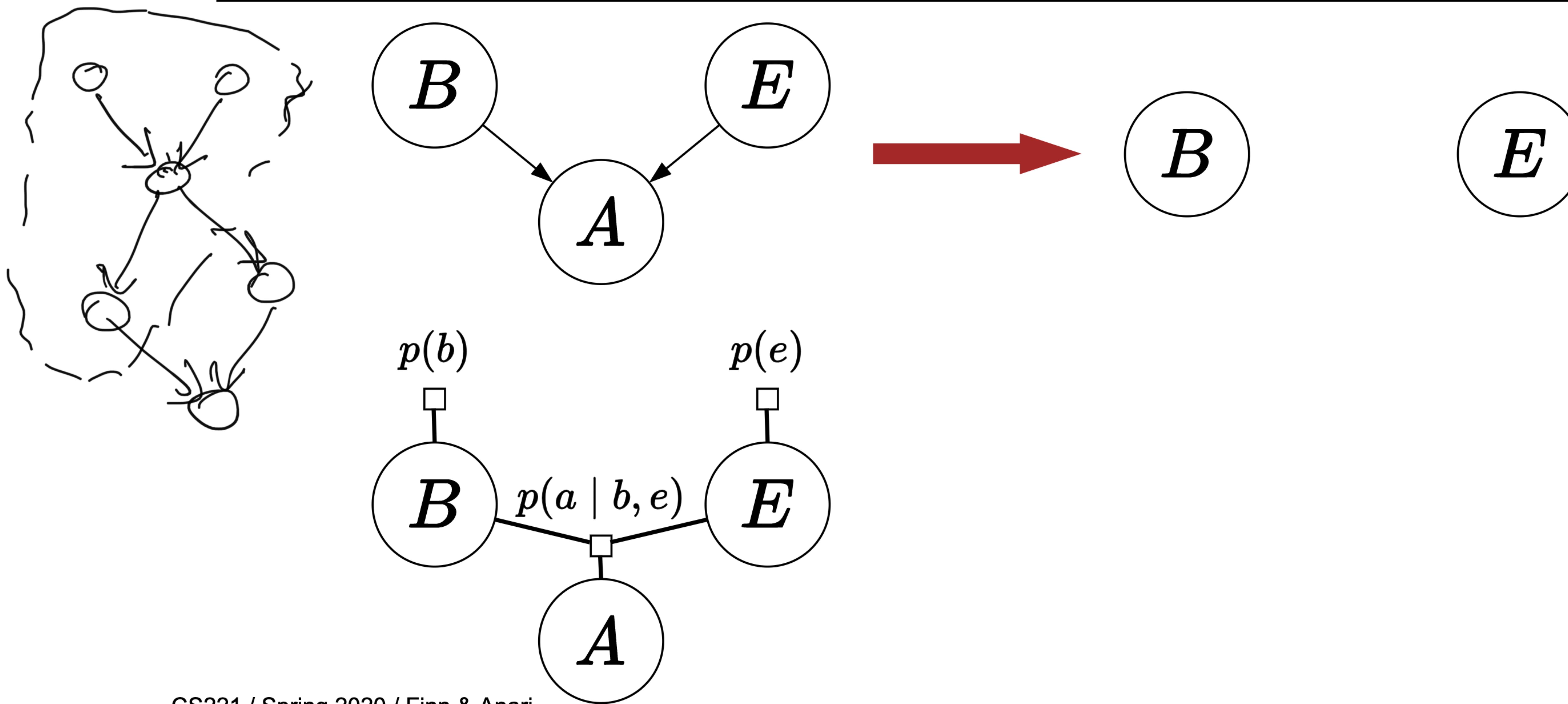
$$= p(b)p(e)$$

Consistency of sub-Bayesian networks



Key idea: marginalization

Marginalization of a leaf node yields a Bayesian network without the node.

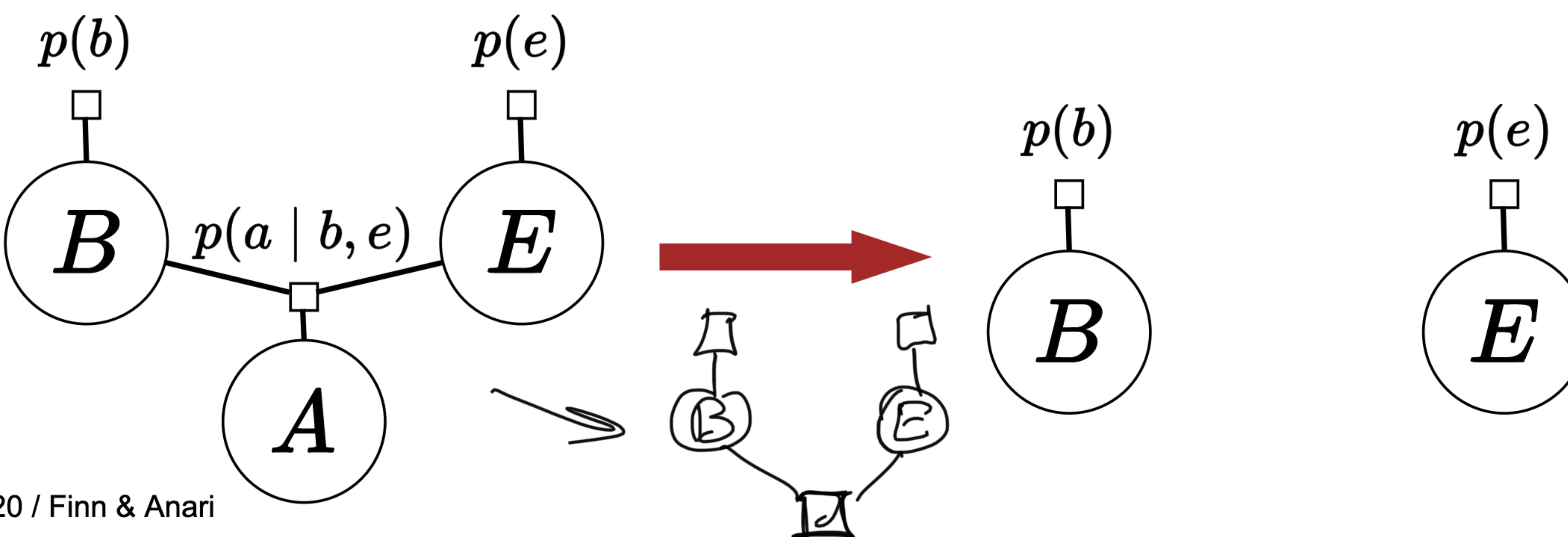
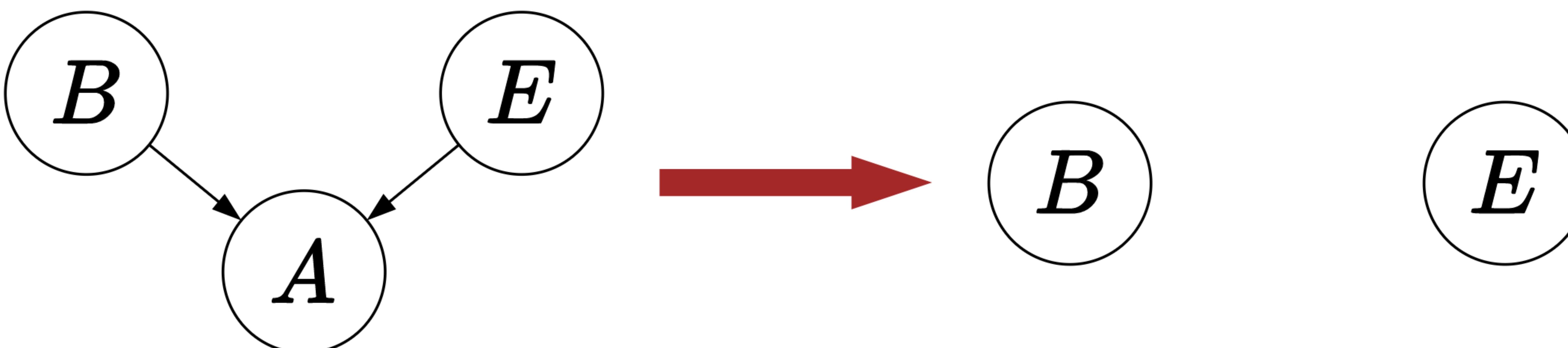


Consistency of sub-Bayesian networks



Key idea: marginalization

Marginalization of a leaf node yields a Bayesian network without the node.

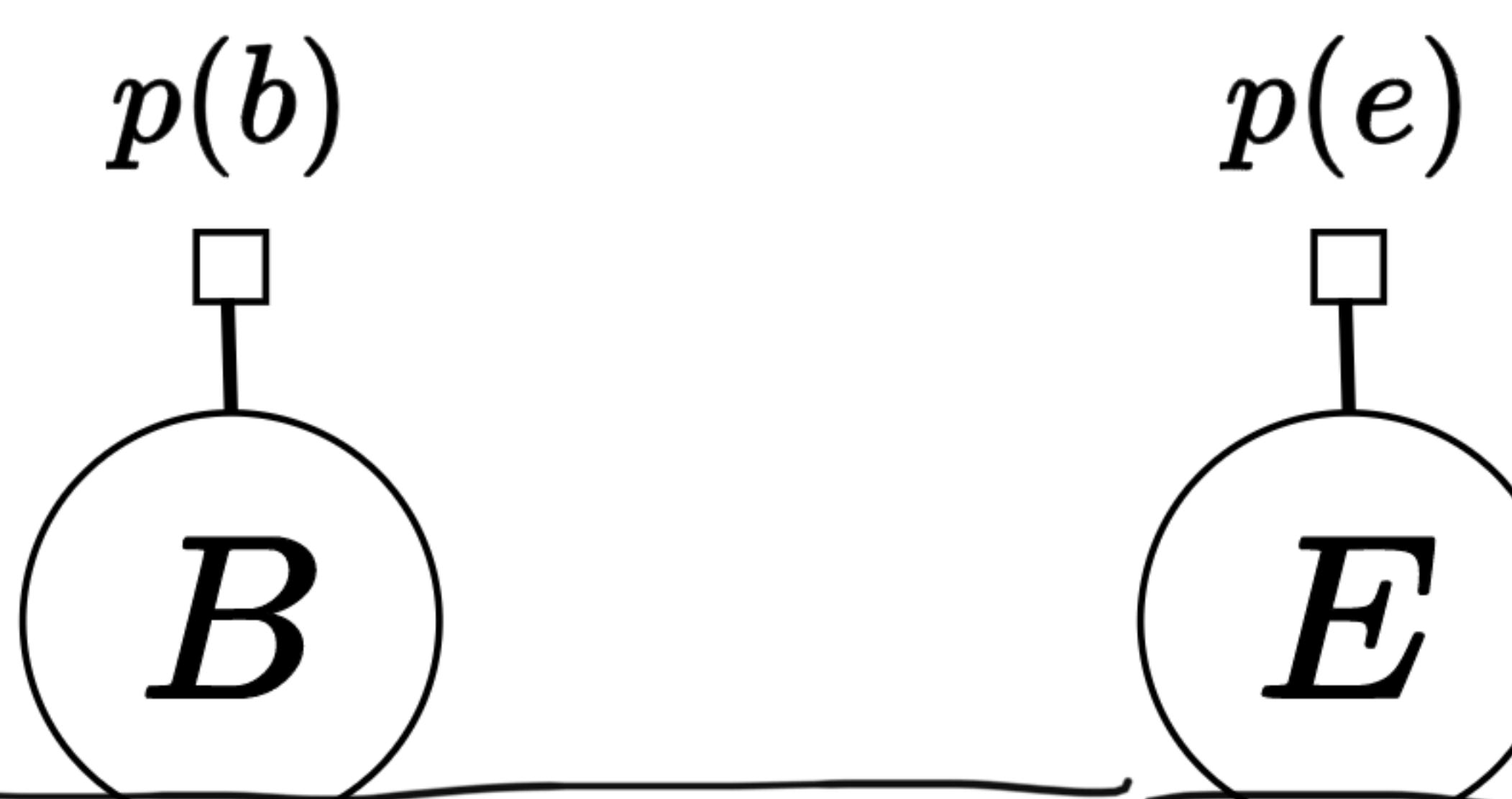
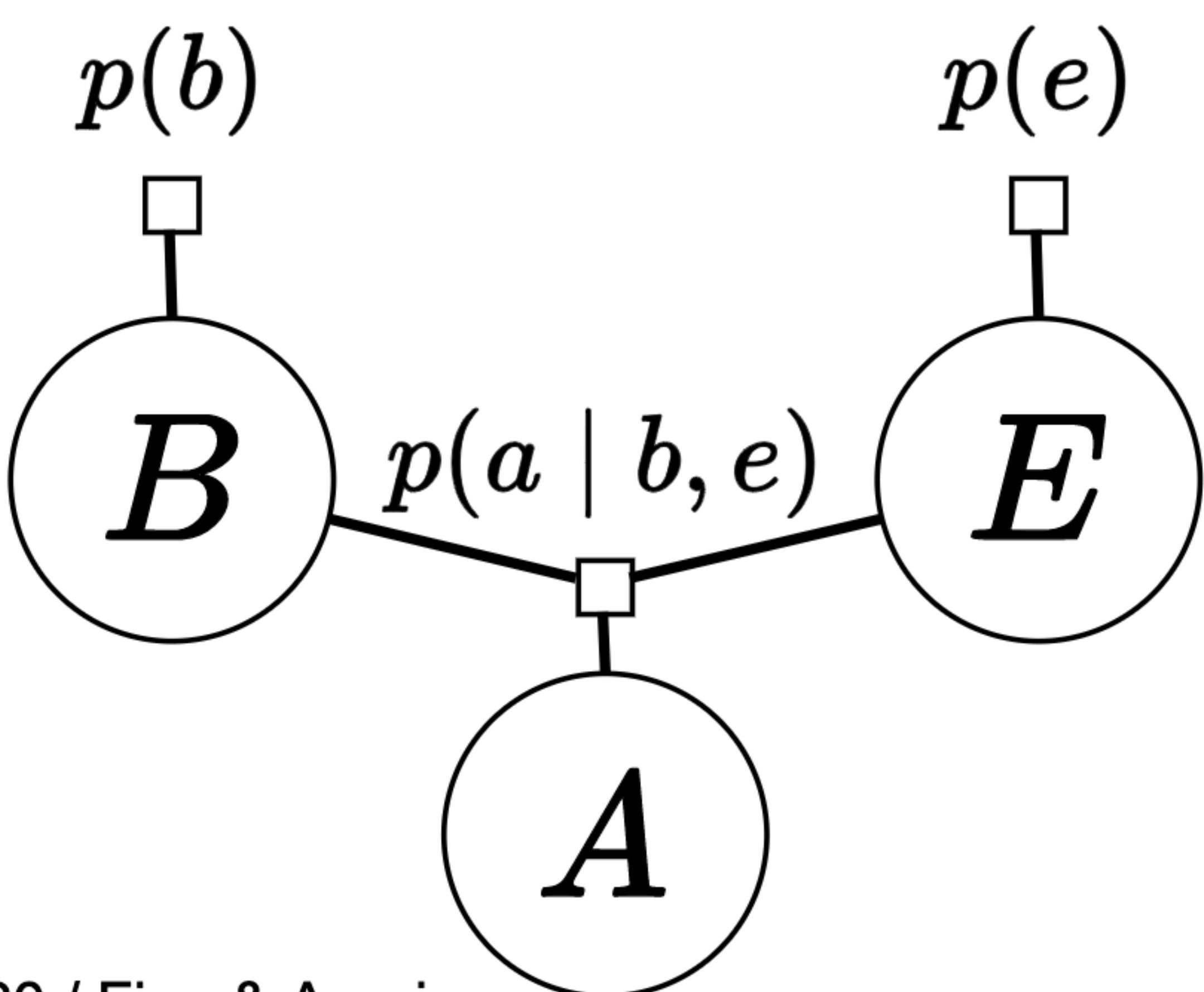
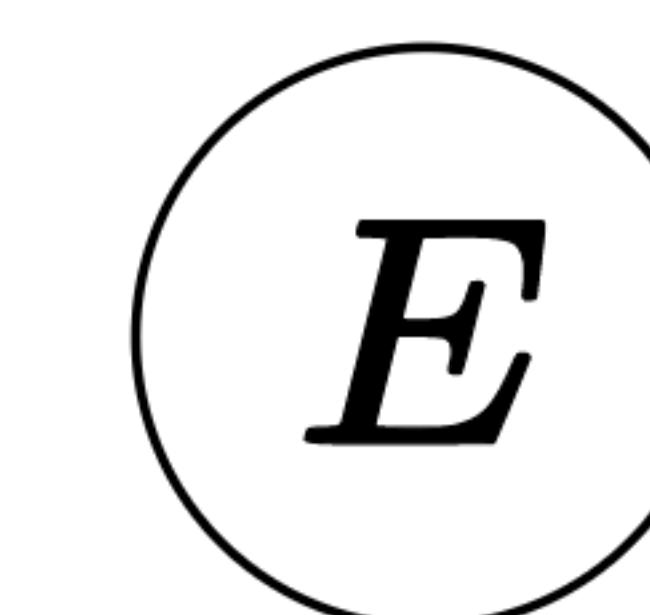
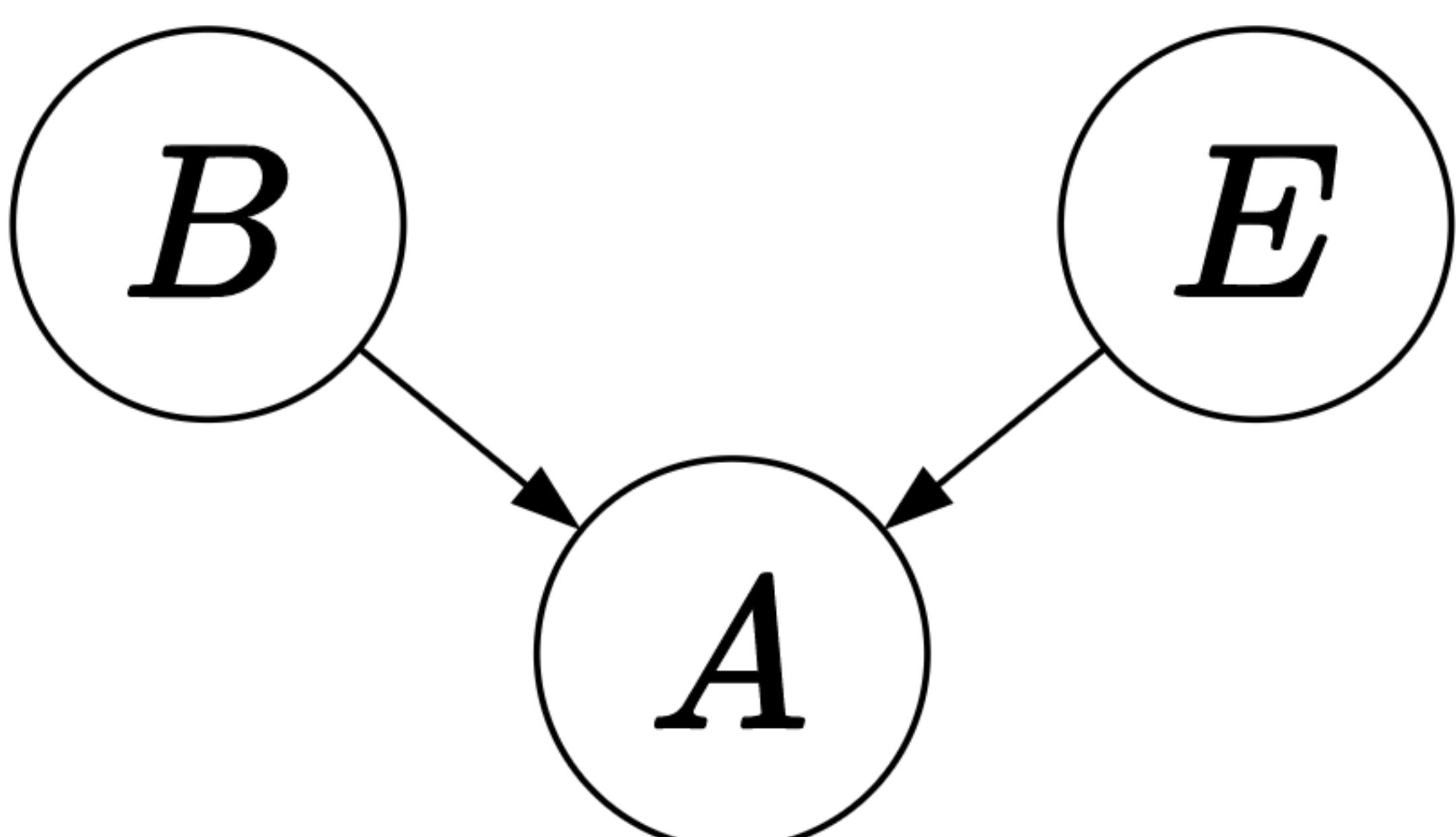


Consistency of sub-Bayesian networks



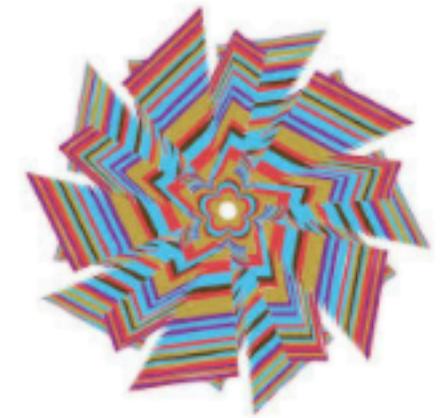
Key idea: marginalization

Marginalization of a leaf node yields a Bayesian network without the node.



$$f_A = \max_{\alpha} \sum_{\alpha} f_1(a, b) \cdot f_2(a, c)$$

Probabilistic program: example



Probabilistic program: object tracking

$$X_0 = (0, 0)$$

For each time step $i = 1, \dots, n$:

With probability α :

$$X_i = X_{i-1} + (1, 0) \text{ [go right]}$$

With probability $1 - \alpha$:

$$X_i = X_{i-1} + (0, 1) \text{ [go down]}$$



Review: probabilistic inference

Input

Bayesian network: $\mathbb{P}(X_1, \dots, X_n)$

Evidence: $E = e$ where $E \subseteq X$ is subset of variables

Query: $Q \subseteq X$ is subset of variables



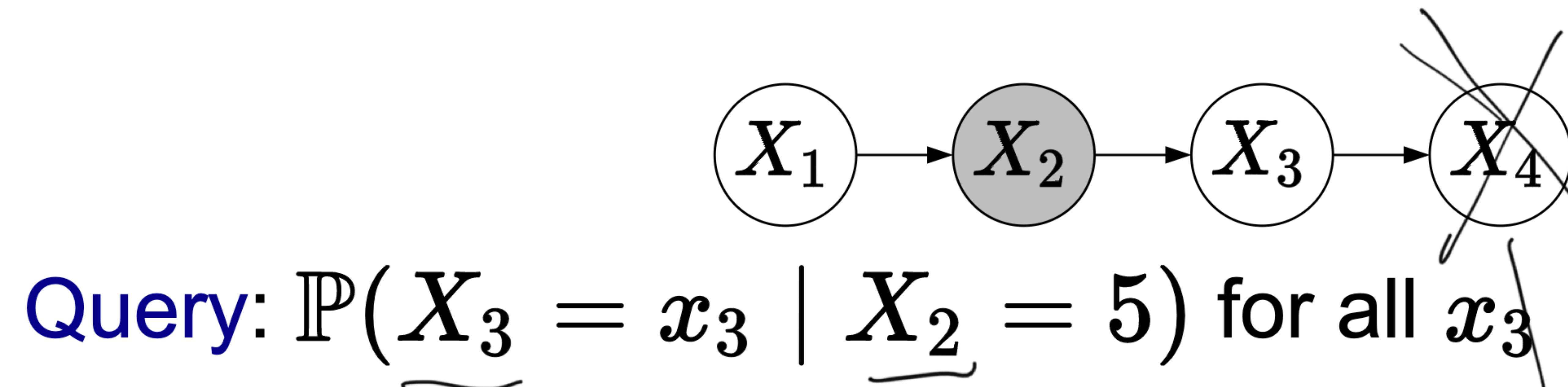
Output

$\mathbb{P}(Q | E = e)$

|||

$\mathbb{P}(Q=q | E=e)$ for all q .

Example: Markov model



Tedious way:

$$\propto \sum_{x_1, x_4} p(x_1)p(x_2 = 5 \mid x_1)p(x_3 \mid x_2 = 5)p(x_4 \mid x_3)$$

$$\propto \left(\sum_{x_1} p(x_1)p(x_2 = 5 \mid x_1) \right) p(x_3 \mid x_2 = 5)$$

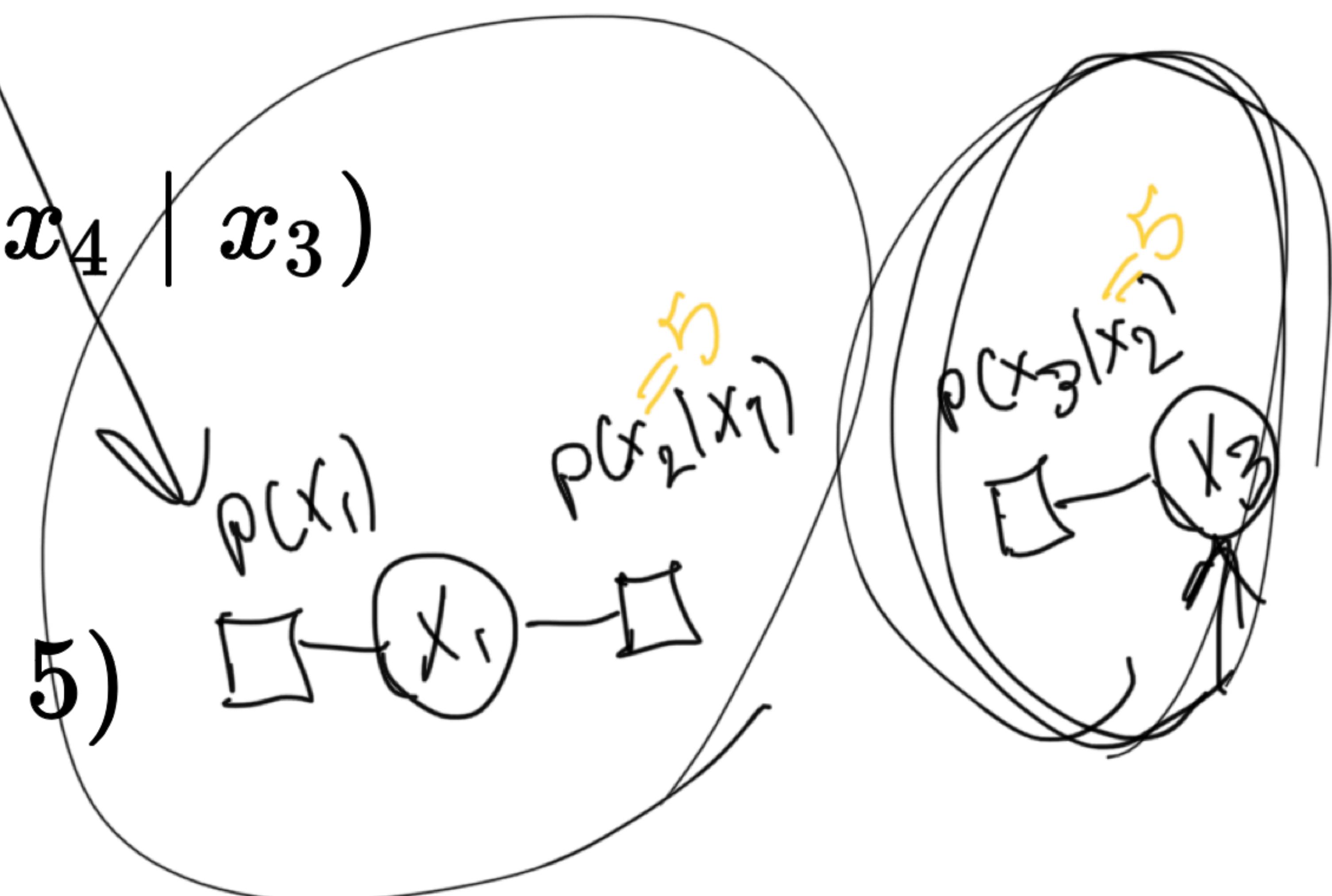
$$\propto p(x_3 \mid x_2 = 5)$$

Fast way:

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1. Eliminate all non-ancestors

2.



General strategy

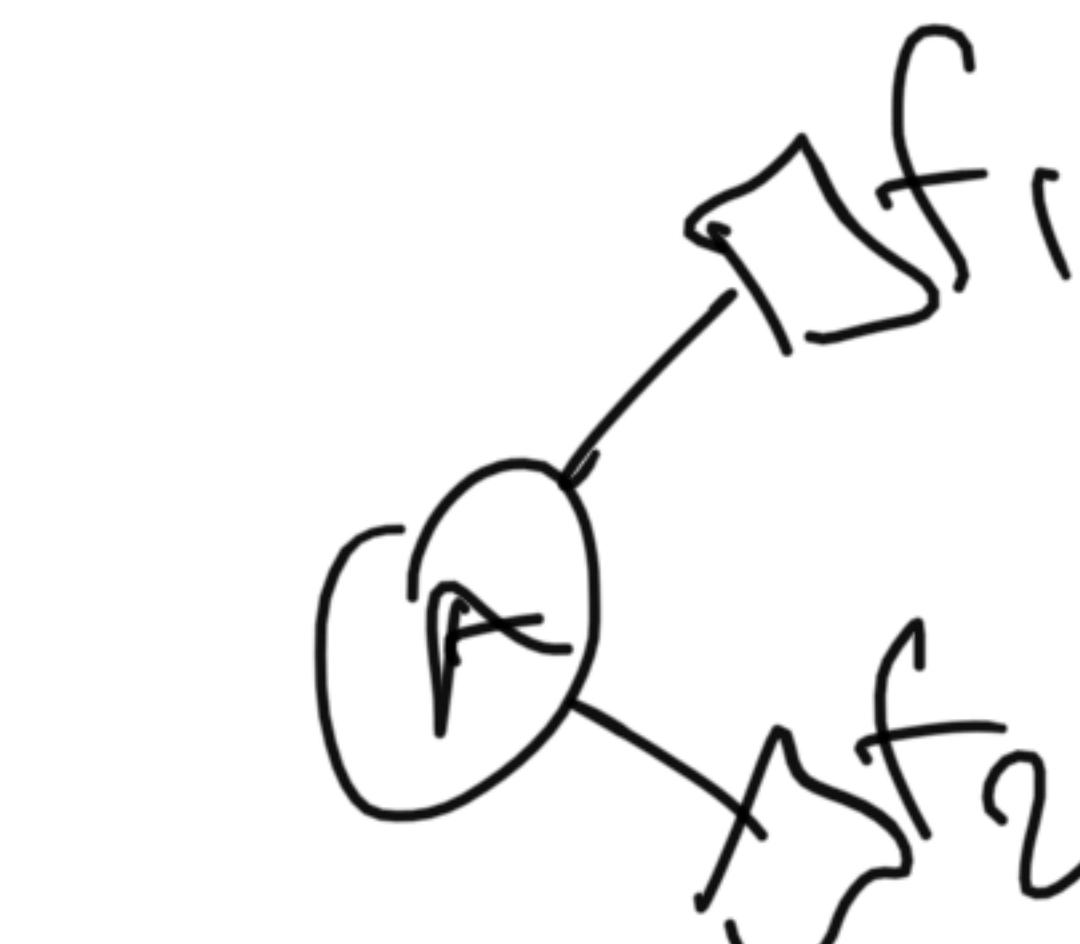
Query:

$$\mathbb{P}(Q \mid E = e)$$



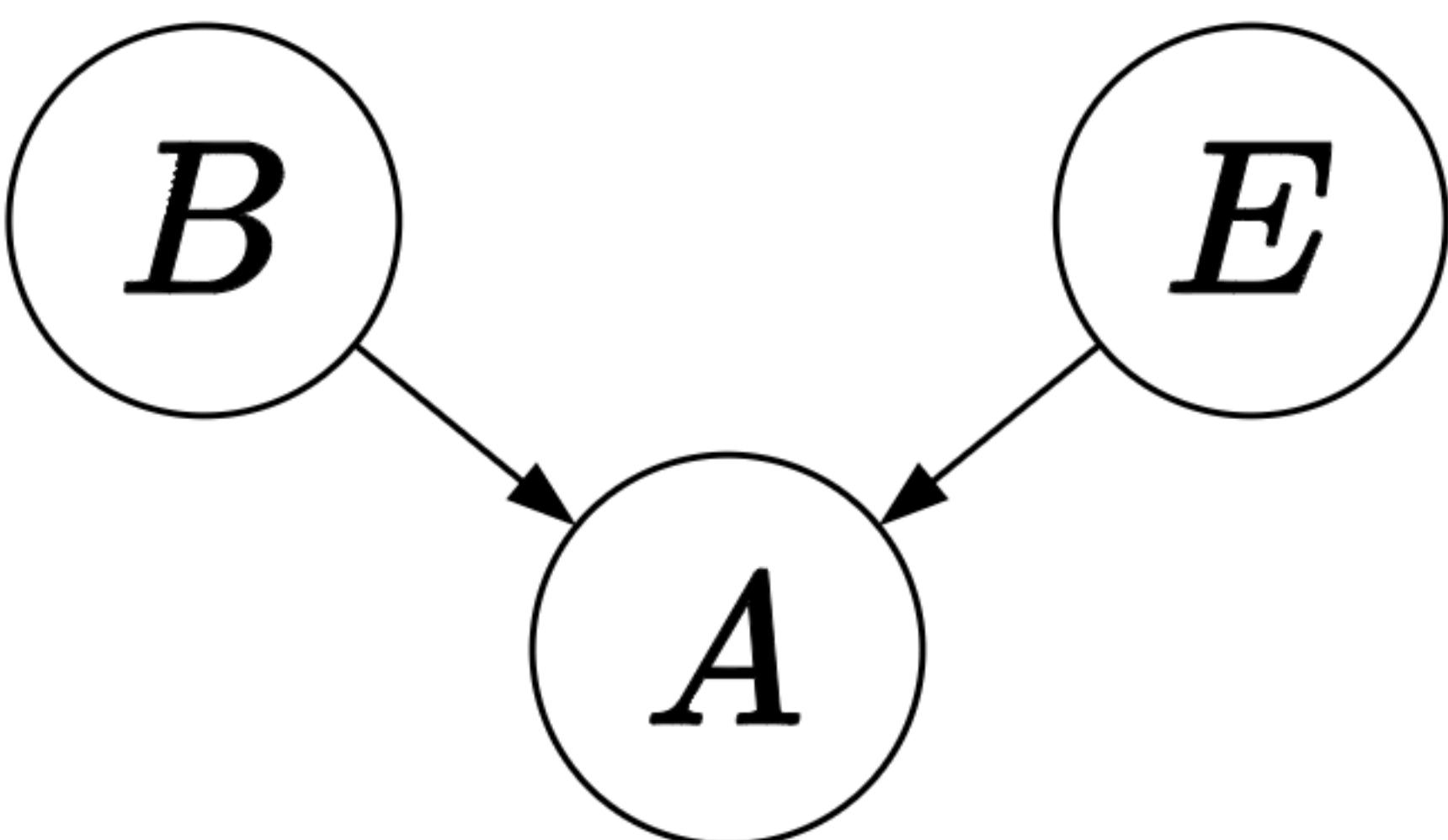
Algorithm: general probabilistic inference strategy

- Remove (marginalize) variables that are not ancestors of Q or E (sub-Bayesian network).
- Convert Bayesian network to factor graph.
- Condition on $E = e$ (shade nodes + disconnect).
- Remove (marginalize) nodes disconnected from Q .



$$\sum_{a \in \text{Domain}(A)} f_i f_2$$

Example: alarm



b	$p(b)$
1	ϵ
0	$1 - \epsilon$

e	$p(e)$
1	ϵ
0	$1 - \epsilon$

b	e	a	$p(a b, e)$
0	0	0	1
0	0	1	0
0	1	0	0
0	1	1	1
1	0	0	0
1	0	1	1
1	1	0	0
1	1	1	1

[whiteboard]

Query: $\mathbb{P}(B)$

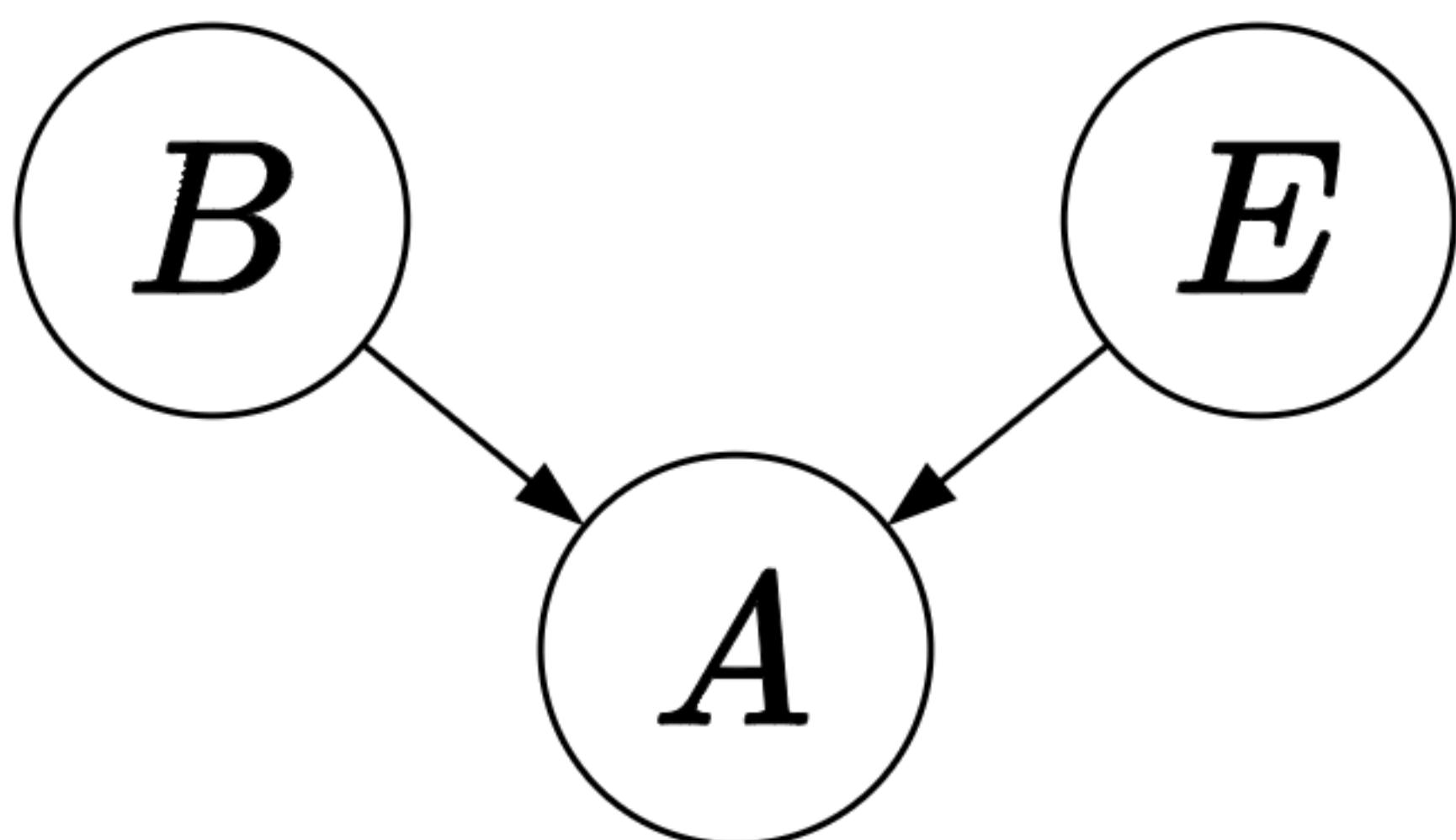
- Marginalize out A, E

Query: $\mathbb{P}(B | A = 1)$

- Condition on $A = 1$



Example: alarm



b	$p(b)$
1	ϵ
0	$1 - \epsilon$

e	$p(e)$
1	ϵ
0	$1 - \epsilon$

b	e	a	$p(a b, e)$
0	0	0	1
0	0	1	0
0	1	0	0
0	1	1	1
1	0	0	0
1	0	1	1
1	1	0	0
1	1	1	1

$$P(B) = \sum_e P(e) \cdot P(a=1 | b, e)$$

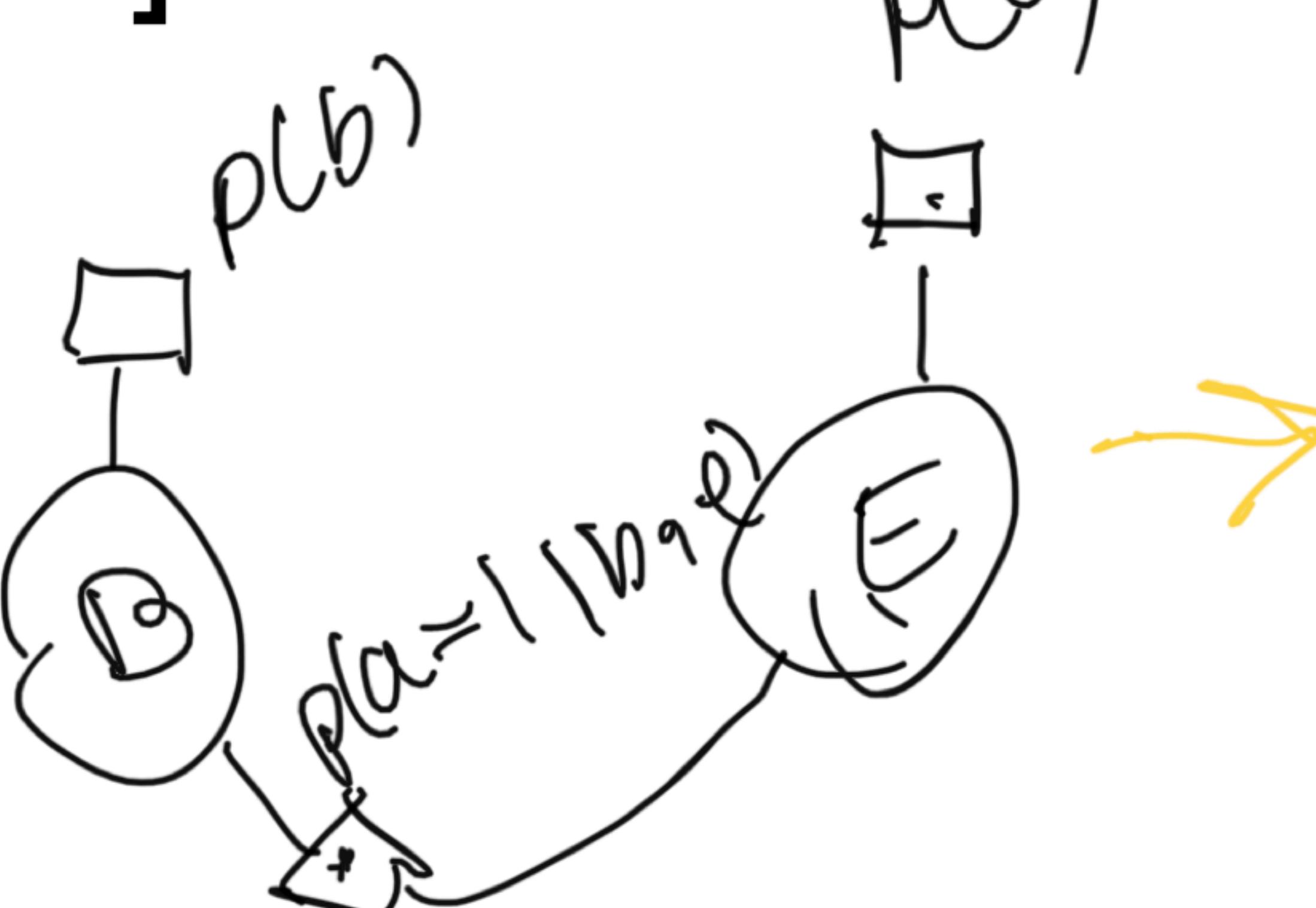
[whiteboard]

Query: $P(B)$

- Marginalize out A, E

Query: $P(B | A = 1) \leftarrow$

- Condition on $A = 1$



$$f(b) = \sum_e p(e) \cdot P(a=1 | b, e)$$

