

FAI LAB 13 1

Probability Theory & Bayesian Networks

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2024-25

- Schedule: Wednesday (or Friday) 11.30 - 13.30
- Material: <https://paolomorettin.github.io/>
- Contact: paolo.morettin@unitn.it (put [FAI lab] in subject)
- Interactive exercise sessions

Probability theory

Probability model:

- For every *possible world* $\omega \in \Omega$: $\mathbb{P}(\omega) \in [0, 1]$
- $\sum_{\omega \in \Omega} \mathbb{P}(\omega) = 1$
- Atomic representation ω : **impractical**

Probability theory

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- $\sum_{\omega \in \Omega} \mathbb{P}(\omega) = 1$
- Atomic representation ω : **impractical**

$\mathbb{P}(\text{"Pollo and Paolo both at the conf"}) = 1/5$

$\mathbb{P}(\text{"Pollo at the conf, but Paolo is not"}) = 1/20$

$\mathbb{P}(\text{"Paolo at the conf, but Pollo is not"}) = 3/20$

$\mathbb{P}(\text{"Neither Pollo nor Paolo at the conf"}) = 3/5$



Probability model:

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- $\sum_{\omega \in \Omega} \mathbb{P}(\omega) = 1$
- Atomic representation ω : **impractical**

Better use a **factored** representation of the world:

- X_1, \dots, X_N *random vars* (RVs), each having $\text{dom}(X_i) = \{v_1, \dots, v_{si}\}$
- $\mathbb{P}(X_1, \dots, X_N)$ *joint probability distribution* over the RVs

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- $\mathbf{P}(X_1, \dots, X_N)$ joint probability distribution over the RVs

$\mathbf{P}(Pa, Po)$		Pa	
		\top	\perp
Po	\top	1/5	1/20
	\perp	3/20	3/5

Probability theory

$\mathbf{P}(Pa, Po)$		Pa	
		\top	\perp
Po	\top	$1/5$	$1/20$
	\perp	$3/20$	$3/5$

Basic **rules**:

Probability theory

$\mathbf{P}(Pa, Po)$		Pa	
		\top	\perp
Po	\top	$1/5$	$1/20$
	\perp	$3/20$	$3/5$

Basic **rules**:

- $\mathbf{P}(A) = \sum_{b \in B} \mathbf{P}(A, B = b)$ (marginalization)

Probability theory

$\mathbf{P}(Pa, Po)$		Pa	
		\top	\perp
Po	\top	$1/5$	$1/20$
	\perp	$3/20$	$3/5$

Basic **rules**:

- $\mathbf{P}(A) = \sum_{b \in B} \mathbf{P}(A, B = b)$ (marginalization)

$$\mathbf{P}(Po) = \mathbf{P}(Pa = \top, Po) + \mathbf{P}(Pa = \perp, Po) = \begin{cases} 5/20 & \text{if } Po = \top \\ 15/20 & \text{if } Po = \perp \end{cases}$$

Probability theory

$\mathbf{P}(Pa, Po)$		Pa	
		\top	\perp
Po	\top	1/5	1/20
	\perp	3/20	3/5

Basic **rules**:

- $\mathbf{P}(A) = \sum_{b \in B} \mathbf{P}(A, B = b)$ (marginalization)

$$\mathbf{P}(Po) = \mathbf{P}(Pa = \top, Po) + \mathbf{P}(Pa = \perp, Po) = \begin{cases} 5/20 & \text{if } Po = \top \\ 15/20 & \text{if } Po = \perp \end{cases}$$

- $\mathbf{P}(A | B = b) = \mathbf{P}(A, B = b) / \mathbf{P}(B = b)$ (conditional probability)

Probability theory

$\mathbf{P}(Pa, Po)$		Pa	
		\top	\perp
Po	\top	$1/5$	$1/20$
	\perp	$3/20$	$3/5$

Basic **rules**:

- $\mathbf{P}(A) = \sum_{b \in B} \mathbf{P}(A, B = b)$ (marginalization)

$$\mathbf{P}(Po) = \mathbf{P}(Pa = \top, Po) + \mathbf{P}(Pa = \perp, Po) = \begin{cases} 5/20 & \text{if } Po = \top \\ 15/20 & \text{if } Po = \perp \end{cases}$$

- $\mathbf{P}(A | B = b) = \mathbf{P}(A, B = b) / \mathbf{P}(B = b)$ (conditional probability)

$$\mathbf{P}(Po | Pa = \top) = \mathbf{P}(Pa = \top, Po) / \mathbf{P}(Pa = \top)$$

Probability theory

$\mathbf{P}(Pa, Po)$		Pa	
		\top	\perp
Po	\top	$1/5$	$1/20$
	\perp	$3/20$	$3/5$

Basic **rules**:

- $\mathbf{P}(A) = \sum_{b \in B} \mathbf{P}(A, B = b)$ (marginalization)

$$\mathbf{P}(Po) = \mathbf{P}(Pa = \top, Po) + \mathbf{P}(Pa = \perp, Po) = \begin{cases} 5/20 & \text{if } Po = \top \\ 15/20 & \text{if } Po = \perp \end{cases}$$

- $\mathbf{P}(A | B = b) = \mathbf{P}(A, B = b) / \mathbf{P}(B = b)$ (conditional probability)

$$\mathbf{P}(Po | Pa = \top) = \mathbf{P}(Pa = \top, Po) / \mathbf{P}(Pa = \top)$$

$$= \frac{\mathbf{P}(Pa = \top, Po)}{7/20} = \begin{cases} 4/7 & \text{if } Po = \top \\ 3/7 & \text{if } Po = \perp \end{cases}$$

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A = \top, B = \top, C = \perp)$

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A = \top, B = \top, C = \perp)$

0

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A = \top, B = \top, C = \perp)$ 0
- $\mathbf{P}(A = \top, B = \top)$

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A = \top, B = \top, C = \perp)$ 0
- $\mathbf{P}(A = \top, B = \top)$ 1/5

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A = \top, B = \top, C = \perp)$ 0
- $\mathbf{P}(A = \top, B = \top)$ 1/5
- $\mathbf{P}(A = \top)$

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A = \top, B = \top, C = \perp)$ 0
- $\mathbf{P}(A = \top, B = \top)$ 1/5
- $\mathbf{P}(A = \top)$ 2/5

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A = \top, B = \top, C = \perp)$ 0
- $\mathbf{P}(A = \top, B = \top)$ 1/5
- $\mathbf{P}(A = \top)$ 2/5
- $\mathbf{P}(A = \top | B = \top)$

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A = \top, B = \top, C = \perp)$ 0
- $\mathbf{P}(A = \top, B = \top)$ 1/5
- $\mathbf{P}(A = \top)$ 2/5
- $\mathbf{P}(A = \top | B = \top)$ 2/7

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A = \top, B = \top, C = \perp)$ 0
- $\mathbf{P}(A = \top, B = \top)$ 1/5
- $\mathbf{P}(A = \top)$ 2/5
- $\mathbf{P}(A = \top | B = \top)$ 2/7
- $\mathbf{P}(B = \top | A = \top)$

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A = \top, B = \top, C = \perp)$ 0
- $\mathbf{P}(A = \top, B = \top)$ 1/5
- $\mathbf{P}(A = \top)$ 2/5
- $\mathbf{P}(A = \top | B = \top)$ 2/7
- $\mathbf{P}(B = \top | A = \top)$ 1/2

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A = \top, B = \top, C = \perp)$ 0
- $\mathbf{P}(A = \top, B = \top)$ 1/5
- $\mathbf{P}(A = \top)$ 2/5
- $\mathbf{P}(A = \top | B = \top)$ 2/7
- $\mathbf{P}(B = \top | A = \top)$ 1/2
- $\mathbf{P}(C = \top | A = \top, B = \top)$

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A = \top, B = \top, C = \perp)$ 0
- $\mathbf{P}(A = \top, B = \top)$ 1/5
- $\mathbf{P}(A = \top)$ 2/5
- $\mathbf{P}(A = \top | B = \top)$ 2/7
- $\mathbf{P}(B = \top | A = \top)$ 1/2
- $\mathbf{P}(C = \top | A = \top, B = \top)$ 1

Probability theory exercises

$$\mathbf{P}(B \mid C = c) = \frac{\sum_a \mathbf{P}(A = a, B, C = c)}{\mathbf{P}(C = c)}$$

About **normalization**:

$$\mathbf{P}(B \mid C = c) = \frac{\sum_a \mathbf{P}(A = a, B, C = c)}{\mathbf{P}(C = c)}$$

About **normalization**:

- $\mathbf{P}(C = c) = \alpha$ is a constant wrt c
- it only serves as a **normalization** factor

Probability theory exercises

$$\mathbf{P}(B \mid C = c) = \frac{\sum_a \mathbf{P}(A = a, B, C = c)}{\mathbf{P}(C = c)}$$

About **normalization**:

- $\mathbf{P}(C = c) = \alpha$ is a constant wrt c
- it only serves as a **normalization** factor
- Can be **computed last**:

1) We compute $\tilde{\mathbf{P}}(B \mid C = c) = \sum_a \mathbf{P}(A = a, B, C = c)$

2) We normalize $\mathbf{P}(B \mid C = c) = \alpha \cdot \tilde{\mathbf{P}}(B \mid C = c)$

with $\alpha = \frac{1}{\sum_b \tilde{\mathbf{P}}(B = b \mid C = c)}$

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A | B = \top, C = \perp)$

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A \mid B = \top, C = \perp)$

$$\alpha \cdot \begin{bmatrix} 0 \\ 2/10 \end{bmatrix} \quad (\alpha = 5)$$

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A \mid B = \top, C = \perp)$ $\alpha \cdot \begin{bmatrix} 0 \\ 2/10 \end{bmatrix}$ ($\alpha = 5$)
- $\mathbf{P}(A \mid B = \top)$

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A | B = \top, C = \perp)$ $\alpha \cdot \begin{bmatrix} 0 \\ 2/10 \end{bmatrix}$ ($\alpha = 5$)
- $\mathbf{P}(A | B = \top)$ $\alpha \cdot \left(\begin{bmatrix} 2/10 \\ 3/10 \end{bmatrix} + \begin{bmatrix} 0 \\ 2/10 \end{bmatrix} \right) = \alpha \cdot \begin{bmatrix} 2/10 \\ 5/10 \end{bmatrix}$ ($\alpha = 10/7$)

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A | B = \top, C = \perp)$ $\alpha \cdot \begin{bmatrix} 0 \\ 2/10 \end{bmatrix}$ ($\alpha = 5$)
- $\mathbf{P}(A | B = \top)$ $\alpha \cdot \left(\begin{bmatrix} 2/10 \\ 3/10 \end{bmatrix} + \begin{bmatrix} 0 \\ 2/10 \end{bmatrix} \right) = \alpha \cdot \begin{bmatrix} 2/10 \\ 5/10 \end{bmatrix}$ ($\alpha = 10/7$)
- $\mathbf{P}(A)$

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A | B = \top, C = \perp)$ $\alpha \cdot \begin{bmatrix} 0 \\ 2/10 \end{bmatrix}$ ($\alpha = 5$)
- $\mathbf{P}(A | B = \top)$ $\alpha \cdot \left(\begin{bmatrix} 2/10 \\ 3/10 \end{bmatrix} + \begin{bmatrix} 0 \\ 2/10 \end{bmatrix} \right) = \alpha \cdot \begin{bmatrix} 2/10 \\ 5/10 \end{bmatrix}$ ($\alpha = 10/7$)
- $\mathbf{P}(A)$ $\alpha \cdot \left(\begin{bmatrix} 2/10 \\ 3/10 \end{bmatrix} + \begin{bmatrix} 0 \\ 1/10 \end{bmatrix} + \begin{bmatrix} 0 \\ 2/10 \end{bmatrix} + \begin{bmatrix} 2/10 \\ 0 \end{bmatrix} \right) = \begin{bmatrix} 4/10 \\ 6/10 \end{bmatrix}$ ($\alpha = 1$)

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A | B = \top, C = \perp)$ $\alpha \cdot \begin{bmatrix} 0 \\ 2/10 \end{bmatrix}$ ($\alpha = 5$)
- $\mathbf{P}(A | B = \top)$ $\alpha \cdot \left(\begin{bmatrix} 2/10 \\ 3/10 \end{bmatrix} + \begin{bmatrix} 0 \\ 2/10 \end{bmatrix} \right) = \alpha \cdot \begin{bmatrix} 2/10 \\ 5/10 \end{bmatrix}$ ($\alpha = 10/7$)
- $\mathbf{P}(A)$ $\alpha \cdot \left(\begin{bmatrix} 2/10 \\ 3/10 \end{bmatrix} + \begin{bmatrix} 0 \\ 1/10 \end{bmatrix} + \begin{bmatrix} 0 \\ 2/10 \end{bmatrix} + \begin{bmatrix} 2/10 \\ 0 \end{bmatrix} \right) = \begin{bmatrix} 4/10 \\ 6/10 \end{bmatrix}$ ($\alpha = 1$)
- $\mathbf{P}(B | A = \top)$

Probability theory exercises

$\mathbf{P}(A, B, C)$	$A = \top$		$A = \perp$	
	$B = \top$	$B = \perp$	$B = \top$	$B = \perp$
$C = \top$	2/10	0/10	3/10	1/10
$C = \perp$	0/10	2/10	2/10	0/10

Compute:

- $\mathbf{P}(A | B = \top, C = \perp)$ $\alpha \cdot \begin{bmatrix} 0 \\ 2/10 \end{bmatrix}$ ($\alpha = 5$)
- $\mathbf{P}(A | B = \top)$ $\alpha \cdot \left(\begin{bmatrix} 2/10 \\ 3/10 \end{bmatrix} + \begin{bmatrix} 0 \\ 2/10 \end{bmatrix} \right) = \alpha \cdot \begin{bmatrix} 2/10 \\ 5/10 \end{bmatrix}$ ($\alpha = 10/7$)
- $\mathbf{P}(A)$ $\alpha \cdot \left(\begin{bmatrix} 2/10 \\ 3/10 \end{bmatrix} + \begin{bmatrix} 0 \\ 1/10 \end{bmatrix} + \begin{bmatrix} 0 \\ 2/10 \end{bmatrix} + \begin{bmatrix} 2/10 \\ 0 \end{bmatrix} \right) = \begin{bmatrix} 4/10 \\ 6/10 \end{bmatrix}$ ($\alpha = 1$)
- $\mathbf{P}(B | A = \top)$ $\alpha \cdot \left(\begin{bmatrix} 2/10 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 2/10 \end{bmatrix} \right) = \begin{bmatrix} 2/10 \\ 2/10 \end{bmatrix}$ ($\alpha = 10/4$)

Probability theory exercises

$$\mathbf{P}(Cause \mid Effect) = \frac{\mathbf{P}(Effect \mid Cause) \cdot \mathbf{P}(Cause)}{\mathbf{P}(Effect)} \text{ (Bayes' rule)}$$

Ex.:

- 25% of the population has a flu
- 9 out of 10 positives to flu have cough
- 2 out of 10 negatives to flu have cough

What is $\mathbf{P}(Flu = \top \mid Cough = \top)$?

What is $\mathbf{P}(Flu = \top \mid Cough = \perp)$?

What is $\mathbf{P}(Flu = \perp \mid Cough = \top)$?

Probability theory exercises

$$\mathbf{P}(Cause \mid Effect) = \frac{\mathbf{P}(Effect \mid Cause) \cdot \mathbf{P}(Cause)}{\mathbf{P}(Effect)} \text{ (Bayes' rule)}$$

Ex.:

- 25% of the population has a flu
- 9 out of 10 positives to flu have cough
- 2 out of 10 negatives to flu have cough

What is $\mathbf{P}(Flu = \top \mid Cough = \top)$?

3/5

What is $\mathbf{P}(Flu = \top \mid Cough = \perp)$?

What is $\mathbf{P}(Flu = \perp \mid Cough = \top)$?

Probability theory exercises

$$\mathbf{P}(Cause \mid Effect) = \frac{\mathbf{P}(Effect \mid Cause) \cdot \mathbf{P}(Cause)}{\mathbf{P}(Effect)} \text{ (Bayes' rule)}$$

Ex.:

- 25% of the population has a flu
- 9 out of 10 positives to flu have cough
- 2 out of 10 negatives to flu have cough

What is $\mathbf{P}(Flu = \top \mid Cough = \top)$?

3/5

What is $\mathbf{P}(Flu = \top \mid Cough = \perp)$?

1/25

What is $\mathbf{P}(Flu = \perp \mid Cough = \top)$?

Probability theory exercises

$$\mathbf{P}(Cause \mid Effect) = \frac{\mathbf{P}(Effect \mid Cause) \cdot \mathbf{P}(Cause)}{\mathbf{P}(Effect)} \text{ (Bayes' rule)}$$

Ex.:

- 25% of the population has a flu
- 9 out of 10 positives to flu have cough
- 2 out of 10 negatives to flu have cough

What is $\mathbf{P}(Flu = \top \mid Cough = \top)$?

3/5

What is $\mathbf{P}(Flu = \top \mid Cough = \perp)$?

1/25

What is $\mathbf{P}(Flu = \perp \mid Cough = \top)$?

2/5

Probability theory

$$\mathbf{P}(A, B) = \mathbf{P}(A | B) \cdot \mathbf{P}(B) \text{ (chain rule)}$$

Probability theory

$$\mathbf{P}(A, B) = \mathbf{P}(A | B) \cdot \mathbf{P}(B) \text{ (chain rule)}$$

- We can **factorize** the joint

$$\begin{aligned}\mathbf{P}(An, Pa, Po) &= \mathbf{P}(Po, Pa | An) \cdot \mathbf{P}(An) \\ &= \mathbf{P}(Po | Pa, An) \cdot \mathbf{P}(Pa | An) \cdot \mathbf{P}(An)\end{aligned}$$

Probability theory

$$\mathbf{P}(A, B) = \mathbf{P}(A | B) \cdot \mathbf{P}(B) \text{ (chain rule)}$$

- We can **factorize** the joint

$$\begin{aligned}\mathbf{P}(An, Pa, Po) &= \mathbf{P}(Po, Pa | An) \cdot \mathbf{P}(An) \\ &= \mathbf{P}(Po | Pa, An) \cdot \mathbf{P}(Pa | An) \cdot \mathbf{P}(An)\end{aligned}$$

- Exploit **independencies** among RVs:

- A and B are **independent** ($A \perp\!\!\!\perp B | \emptyset$)

$$\mathbf{P}(A, B) = \mathbf{P}(A) \cdot \mathbf{P}(B) \text{ (equiv. } \mathbf{P}(A | B) = \mathbf{P}(A))$$

- A and B are **conditionally independent** given C ($A \perp\!\!\!\perp B | C$)

$$\mathbf{P}(A, B | C) = \mathbf{P}(A | C) \cdot \mathbf{P}(B | C) \text{ (equiv. } \mathbf{P}(A | B, C) = \mathbf{P}(A | C))$$

Probability theory

$$\mathbf{P}(A, B) = \mathbf{P}(A | B) \cdot \mathbf{P}(B) \text{ (chain rule)}$$

- We can **factorize** the joint

$$\begin{aligned}\mathbf{P}(An, Pa, Po) &= \mathbf{P}(Po, Pa | An) \cdot \mathbf{P}(An) \\ &= \mathbf{P}(Po | Pa, An) \cdot \mathbf{P}(Pa | An) \cdot \mathbf{P}(An)\end{aligned}$$

- Exploit **independencies** among RVs:

- A and B are **independent** ($A \perp\!\!\!\perp B | \emptyset$)

$$\mathbf{P}(A, B) = \mathbf{P}(A) \cdot \mathbf{P}(B) \text{ (equiv. } \mathbf{P}(A | B) = \mathbf{P}(A))$$

- A and B are **conditionally independent** given C ($A \perp\!\!\!\perp B | C$)

$$\mathbf{P}(A, B | C) = \mathbf{P}(A | C) \cdot \mathbf{P}(B | C) \text{ (equiv. } \mathbf{P}(A | B, C) = \mathbf{P}(A | C))$$

- More compact models!

$$Po \perp\!\!\!\perp An | Pa \Rightarrow \mathbf{P}(An, Pa, Po) = \mathbf{P}(Po | Pa) \cdot \mathbf{P}(Pa | An) \cdot \mathbf{P}(An)$$

Bayesian Networks

$$\mathbf{P}(X_1, \dots, X_N) = \prod_i \mathbf{P}(X_i | \text{Pa}(X_i))$$

$$\mathbf{P}(X_1, \dots, X_N) = \prod_i \mathbf{P}(X_i | \text{Pa}(X_i))$$

- **Graphical** representation of the factorization above

$$\mathbf{P}(X_1, \dots, X_N) = \prod_i \mathbf{P}(X_i | \text{Pa}(X_i))$$

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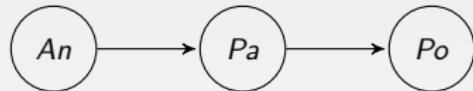
$$\mathbf{P}(X_1, \dots, X_N) = \prod_i \mathbf{P}(X_i | \text{Pa}(X_i))$$

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Bayesian Networks

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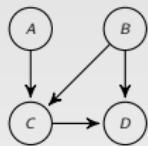


$$\mathbf{P}(An, Pa, Po) = \mathbf{P}(Po | Pa) \cdot \mathbf{P}(Pa | An) \cdot \mathbf{P}(An)$$

$\mathbf{P}(An = \top)$	$\mathbf{P}(Pa = \top An)$	$\mathbf{P}(Po = \top Pa)$
$2/5$	$2/5$	$4/5$
$An = \perp$	$1/4$	$1/10$

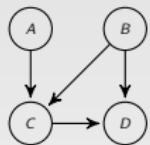
Bayesian Networks exercises

Write $\mathbf{P}(A, B, C, D)$ and min. # of params (with binary RVs):



Bayesian Networks exercises

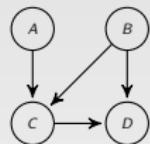
Write $\mathbf{P}(A, B, C, D)$ and min. # of params (with binary RVs):



$$\mathbf{P}(A) \cdot \mathbf{P}(B) \cdot \mathbf{P}(C | A, B) \cdot \mathbf{P}(D | B, C)$$

Bayesian Networks exercises

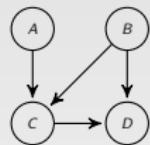
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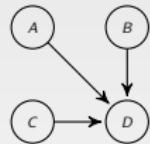
$$\overbrace{\mathbf{P}(A)}^1 \cdot \overbrace{\mathbf{P}(B)}^1 \cdot \overbrace{\mathbf{P}(C | A, B)}^{1 \cdot 2^2} \cdot \overbrace{\mathbf{P}(D | B, C)}^{1 \cdot 2^2}$$

Bayesian Networks exercises

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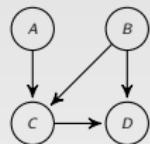


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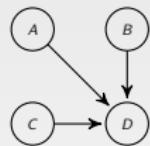


Bayesian Networks exercises

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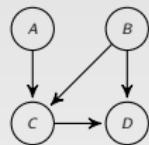
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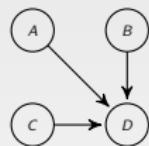
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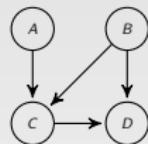
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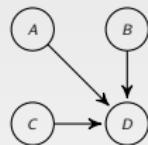
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Bayesian Networks exercises

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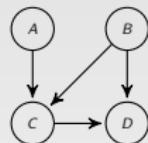


$$\overbrace{\mathbf{P}(A)}^1 \cdot \overbrace{\mathbf{P}(B)}^1 \cdot \overbrace{\mathbf{P}(C)}^1 \cdot \overbrace{\mathbf{P}(D | A, B, C)}^{1 \cdot 2^3}$$

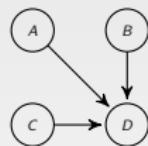


Bayesian Networks exercises

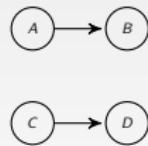
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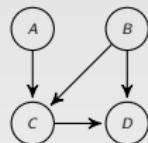
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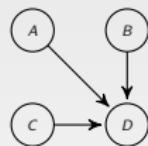
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Bayesian Networks exercises

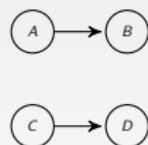
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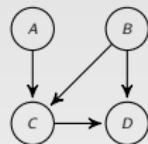
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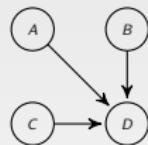
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Bayesian Networks exercises

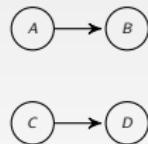
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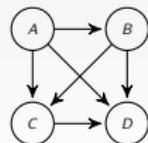
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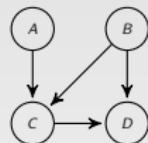


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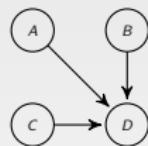


Bayesian Networks exercises

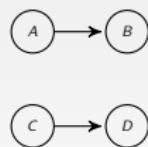
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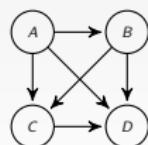
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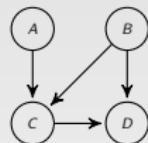
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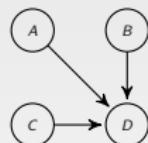
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Bayesian Networks exercises

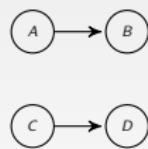
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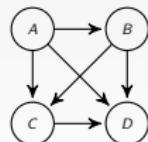
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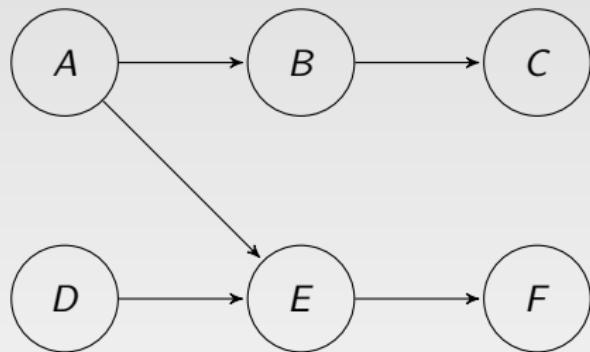


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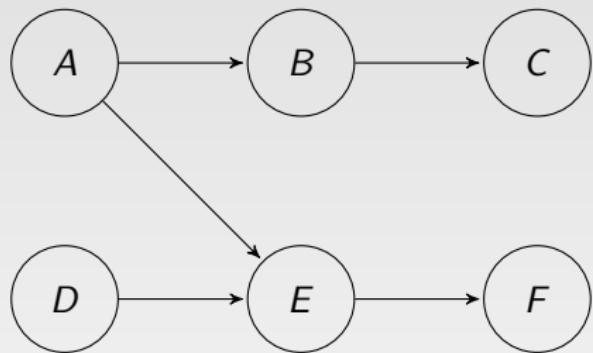


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Bayesian Networks exercises

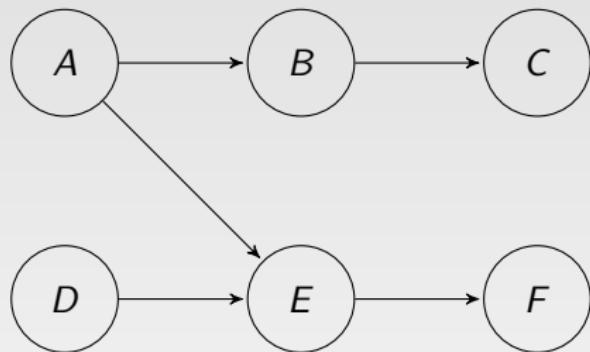


Bayesian Networks exercises



$$\mathbf{P}(A) \cdot \mathbf{P}(D) \cdot \mathbf{P}(B | A) \cdot \mathbf{P}(C | B) \cdot \mathbf{P}(E | A, D) \cdot \mathbf{P}(F | E)$$

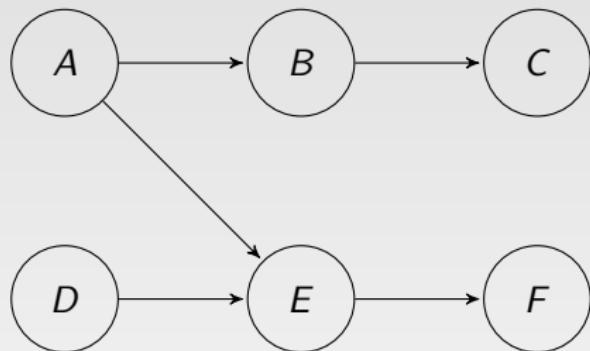
Bayesian Networks exercises



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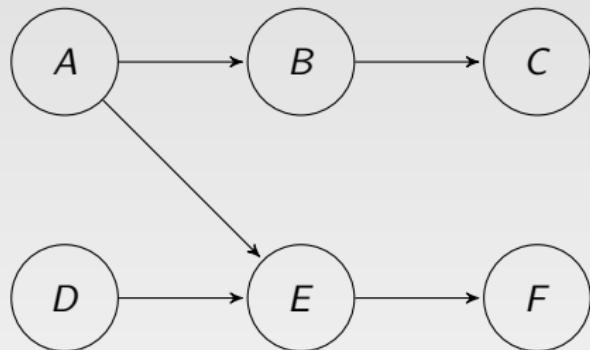
Bayesian Networks exercises



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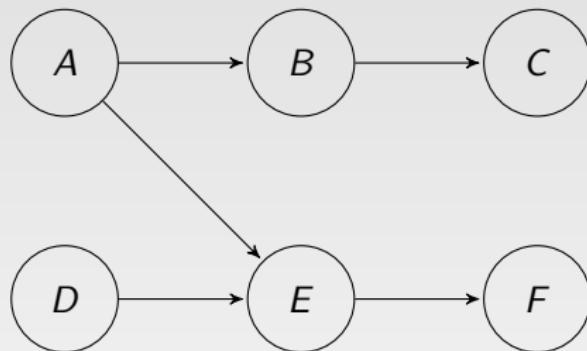
Bayesian Networks exercises



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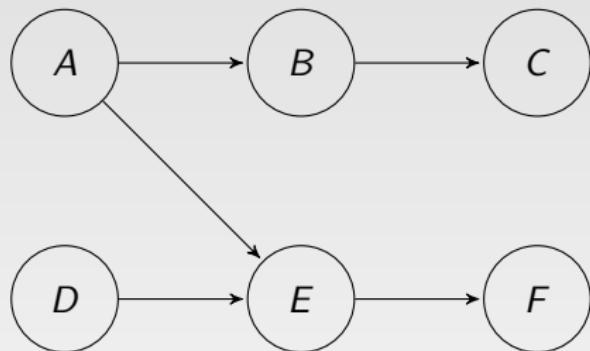
Bayesian Networks exercises



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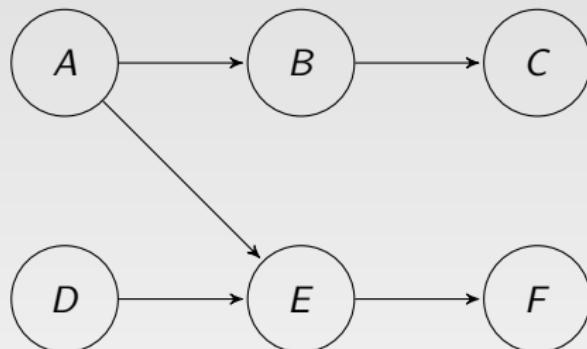
Bayesian Networks exercises



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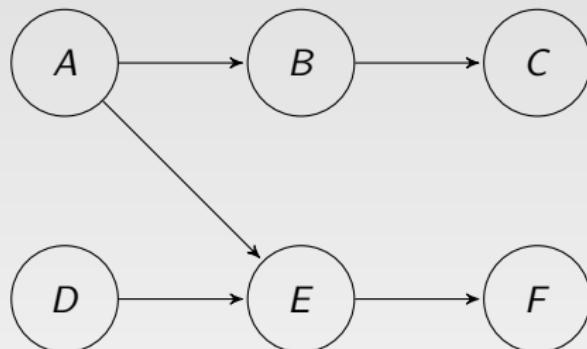
Bayesian Networks exercises



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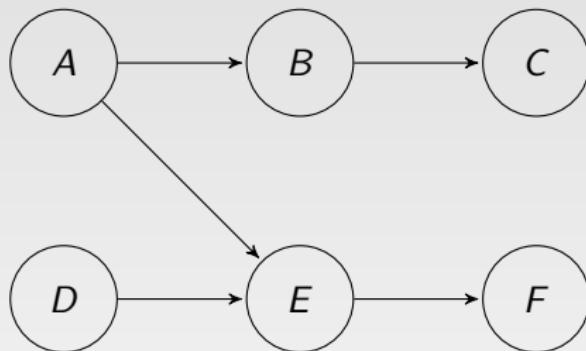
Bayesian Networks exercises



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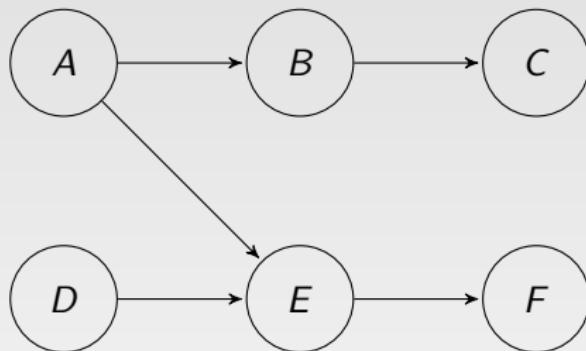
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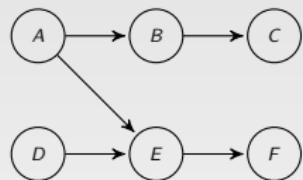
Bayesian Networks exercises



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- $A \perp\!\!\!\perp C?$ $\mathbf{P}(A, C) = \mathbf{P}(A) \cdot \mathbf{P}(C)?$ No
- $A \perp\!\!\!\perp D?$ $\mathbf{P}(A, D) = \mathbf{P}(A) \cdot \mathbf{P}(D)?$ Yes
- $B \perp\!\!\!\perp E | A?$ $\mathbf{P}(B, E | A) = \mathbf{P}(B | A) \cdot \mathbf{P}(E | A)?$ Yes

Bayesian Networks exercises



$$\mathbf{P}(a) = 4/10 \quad \mathbf{P}(d) = 3/10$$

$$\mathbf{P}(b | a) = 6/10 \quad \mathbf{P}(b | \neg a) = 1/10$$

$$\mathbf{P}(c | b) = 5/10 \quad \mathbf{P}(c | \neg b) = 0/10$$

$$\mathbf{P}(e | a, d) = 2/10 \quad \mathbf{P}(e | a, \neg d) = 1/10$$

$$\mathbf{P}(e | \neg a, d) = 2/10 \quad \mathbf{P}(e | \neg a, \neg d) = 4/10$$

$$\mathbf{P}(f | e) = 3/10 \quad \mathbf{P}(f | \neg e) = 4/10$$

- Compute $\mathbf{P}(A | B, E)$
- Using the factors above, compute $\mathbf{P}(A | b, \neg e)$
- Using the factors above, compute $\mathbf{P}(A | b, e)$

Bayesian Networks exercises

$$\mathbf{P}(a) = 4/10 \quad \mathbf{P}(d) = 3/10 \quad \mathbf{P}(b | a) = 6/10 \quad \mathbf{P}(b | \neg a) = 1/10$$

$$\mathbf{P}(e | a, d) = 2/10 \quad \mathbf{P}(e | a, \neg d) = 1/10$$

$$\mathbf{P}(e | \neg a, d) = 2/10 \quad \mathbf{P}(e | \neg a, \neg d) = 4/10$$

$$\begin{aligned}\mathbf{P}(A | B, E) &= \alpha \cdot \sum_C \sum_D \sum_F \mathbf{P}(A, B, C, D, E, F) \\&= \alpha \cdot \mathbf{P}(A) \cdot \mathbf{P}(B | A) \cdot \sum_d \mathbf{P}(D) \cdot \mathbf{P}(E | A, D) \\&= \alpha \cdot \begin{bmatrix} 4/10 \\ 6/10 \end{bmatrix} \cdot \begin{bmatrix} b \\ 6/10 \\ 1/10 \end{bmatrix} \cdot \begin{bmatrix} \neg b \\ 4/10 \\ 9/10 \end{bmatrix} \cdot \left(\frac{3}{10} \cdot \begin{bmatrix} e \\ 2/10 \\ 2/10 \end{bmatrix} + \frac{7}{10} \cdot \begin{bmatrix} e \\ 1/10 \\ 4/10 \end{bmatrix} \cdot \begin{bmatrix} \neg e \\ 9/10 \\ 6/10 \end{bmatrix} \right) \\&= \alpha \cdot \begin{bmatrix} 4/10 \\ 6/10 \end{bmatrix} \cdot \begin{bmatrix} b \\ 6/10 \\ 1/10 \end{bmatrix} \cdot \begin{bmatrix} \neg b \\ 4/10 \\ 9/10 \end{bmatrix} \cdot \begin{bmatrix} e \\ 13/100 \\ 34/100 \end{bmatrix} \cdot \begin{bmatrix} \neg e \\ 87/100 \\ 66/100 \end{bmatrix}\end{aligned}$$

Bayesian Networks exercises

$$\mathbf{P}(E | A, D) = \alpha \cdot \begin{bmatrix} 4/10 \\ 6/10 \end{bmatrix} \cdot \begin{bmatrix} b & \neg b \\ \overbrace{6/10} & \overbrace{4/10} \\ 1/10 & 9/10 \end{bmatrix} \cdot \begin{bmatrix} e & \neg e \\ \overbrace{13/100} & \overbrace{87/100} \\ 34/100 & 66/100 \end{bmatrix}$$

$$\mathbf{P}(A | b, \neg e) = \alpha_{b, \neg e} \cdot \begin{bmatrix} 4/10 \\ 6/10 \end{bmatrix} \cdot \begin{bmatrix} 6/10 \\ 1/10 \end{bmatrix} \cdot \begin{bmatrix} 87/100 \\ 66/100 \end{bmatrix} = \begin{bmatrix} 2088/10000 \\ 396/10000 \end{bmatrix}$$

$$\alpha_{b, \neg e} = \frac{10000}{2484}$$

$$\mathbf{P}(A | b, e) = \alpha_{b, e} \cdot \begin{bmatrix} 4/10 \\ 6/10 \end{bmatrix} \cdot \begin{bmatrix} 6/10 \\ 1/10 \end{bmatrix} \cdot \begin{bmatrix} 13/100 \\ 34/100 \end{bmatrix} = \begin{bmatrix} 312/10000 \\ 204/10000 \end{bmatrix}$$

$$\alpha_{b, e} = \frac{10000}{516}$$