

Bayes' Burrito

(a) How many different types of burrito bowls are there

For each type of rice, it can be paired with 4 types of beans; In terms of the topping combination, the customer would be able to choose any subset of the 7 topping options. Therefore the total number of choices for toppings would be: 2^7 . Combine it together

$$\begin{aligned}\text{Total} &= 2 \times 4 \times 2^7 \\ &= 8 \times 128 \\ &= 1024\end{aligned}$$

Therefore, there are 1024 different types of burrito bowls possible.

(b) Eshan's burrito bowl

The factorization goes as follows:

$$P_{Eshan}(R, B, T) = P(R) \times P(B) \times P(T \mid R, B)$$

- $P(R)$: need 1 independent value (2 possibilities, knowing 1 would imply the other, since the possibilities must sum up to 1)
- $P(B)$: need 3 independent values (similar reason as above)
- $P(T \mid R, B)$: firstly there are 2 options for R , 4 options for B , and 2^7 options for T , therefore for each combination of R, B , need $(2^7 - 1)$ independent values; lastly calculate the conditional probability for $P(T \mid R, B) = 2 \times 4 \times (2^7 - 1) = 1016$

Putting them together, the total number of independent values needed to know is $1 + 3 + 1016 = 1020$. Thus, 1020 values must be known to fully compute $P_{Eshan}(R, B, T)$.

(c) Zafeer's burrito bowl

The factorization goes as follows:

$$P_{Zafeer}(R, B, T) = P(R) \times P(B \mid R) \times P(T)$$

- $P(R)$: need 1 independent value (2 possibilities, knowing 1 would imply the other, since the possibilities must sum up to 1)
- $P(B)$: for each types of rice, have 4 options, but 3 needs calculation (they sum up to 1), therefore the independent values for this conditional probability is $2 \times 3 = 6$
- $P(T \mid R, B)$: need $2^7 - 1 = 127$ independent values (same reason as above)

Putting them together, the total number of independent values needed to know is $1 + 6 + 127 = 134$. Thus, 134 values must be known to fully compute $P_{Zafeer}(R, B, T)$.

Bayesian Network

(a) Variables independent of I

Variables A, B, E, D, F are independent of I

- A, B, E because they are not ancestors or descendants of I , and no path from I to them
- D, F because it is not connected to I and does not share common descendants with I

(b) Variables that are conditionally independent of A given K

Given K , A is conditionally independent of J, I, D, F

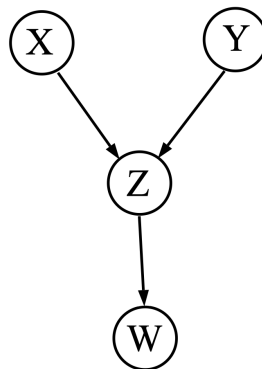
- J because conditioning on K block the path from A to J through K , conditioning on K makes J d-separated from A
- I, D, F because there are no path connecting A to D or F , regardless K is conditioned or not

(c) Variables that are conditionally independent of B given E

Given E , B is conditionally independent of D, I, F

- D because it is a non descendant of B and does not have any influence that has not already being accounted for by E
- I, F because there are no path connecting B to I, F , regardless E is conditioned or not

Drawing a Bayesian Network



Z as the common effect of X, Y , satisfying the condition that X, Y are conditionally independent given Z . When X, Y are both known, Z, W becomes conditionally independent, because X, Y already contains all the information for Z , along with any information that Z will provide for W .

Amazing Race Problem

(a) Calculate all M, N for $P(F = \text{yes} \mid N, M)$

First, consider that there are 2 choices for $M : \{\text{train}, \text{car}\}$ and 3 choices for $N : \{0, 1, 2\}$. Therefore there are 6 possible combinations for making the flight, below it will be calculated separately.

0.1 $M = \text{train}, N = 0$

$$\begin{aligned} P(\text{yes} \mid 0, \text{train}) &= P(\text{yes} \mid \text{early}, \text{fast}) \cdot P(\text{early} \mid \text{train}, 0) \cdot P(\text{fast} \mid 0) \\ &\quad + P(\text{yes} \mid \text{early}, \text{slow}) \cdot P(\text{early} \mid \text{train}, 0) \cdot P(\text{slow} \mid 0) \\ &\quad + P(\text{yes} \mid \text{late}, \text{fast}) \cdot P(\text{late} \mid \text{train}, 0) \cdot P(\text{fast} \mid 0) \\ &\quad + P(\text{yes} \mid \text{late}, \text{slow}) \cdot P(\text{late} \mid \text{train}, 0) \cdot P(\text{fast} \mid 0) \\ &= (0.95 \cdot 0.9 \cdot 0.9) + (0.7 \cdot 0.9 \cdot [1 - 0.9]) + (0.7 \cdot [1 - 0.9] \cdot 0.9) \\ &\quad + (0.35 \cdot [1 - 0.9] \cdot [1 - 0.9]) \\ &= 0.7695 + 0.063 + 0.063 + 0.0035 \\ &= 0.899 \end{aligned}$$

0.2 $M = \text{train}, N = 1$

$$\begin{aligned} P(\text{yes} \mid 1, \text{train}) &= P(\text{yes} \mid \text{early}, \text{fast}) \cdot P(\text{early} \mid \text{train}, 1) \cdot P(\text{fast} \mid 1) \\ &\quad + P(\text{yes} \mid \text{early}, \text{slow}) \cdot P(\text{early} \mid \text{train}, 1) \cdot P(\text{slow} \mid 1) \\ &\quad + P(\text{yes} \mid \text{late}, \text{fast}) \cdot P(\text{late} \mid \text{train}, 1) \cdot P(\text{fast} \mid 1) \\ &\quad + P(\text{yes} \mid \text{late}, \text{slow}) \cdot P(\text{late} \mid \text{train}, 1) \cdot P(\text{fast} \mid 1) \\ &= (0.95 \cdot 0.85 \cdot 0.8) + (0.7 \cdot 0.85 \cdot [1 - 0.8]) + (0.7 \cdot [1 - 0.85] \cdot 0.8) \\ &\quad + (0.35 \cdot [1 - 0.85] \cdot [1 - 0.8]) \\ &= 0.646 + 0.119 + 0.084 + 0.0105 \\ &= 0.8595 \end{aligned}$$

0.3 $M = \text{train}, N = 2$

$$\begin{aligned} P(\text{yes} \mid 2, \text{train}) &= P(\text{yes} \mid \text{early}, \text{fast}) \cdot P(\text{early} \mid \text{train}, 2) \cdot P(\text{fast} \mid 2) \\ &\quad + P(\text{yes} \mid \text{early}, \text{slow}) \cdot P(\text{early} \mid \text{train}, 2) \cdot P(\text{slow} \mid 2) \\ &\quad + P(\text{yes} \mid \text{late}, \text{fast}) \cdot P(\text{late} \mid \text{train}, 2) \cdot P(\text{fast} \mid 2) \\ &\quad + P(\text{yes} \mid \text{late}, \text{slow}) \cdot P(\text{late} \mid \text{train}, 2) \cdot P(\text{fast} \mid 2) \\ &= (0.95 \cdot 0.6 \cdot 0.7) + (0.7 \cdot 0.6 \cdot [1 - 0.7]) + (0.7 \cdot [1 - 0.6] \cdot 0.7) \\ &\quad + (0.35 \cdot [1 - 0.6] \cdot [1 - 0.7]) \\ &= 0.399 + 0.126 + 0.196 + 0.042 \\ &= 0.763 \end{aligned}$$

0.4 $M = car, N = 0$

$$\begin{aligned} P(yes \mid 0, car) &= P(yes \mid early, fast) \cdot P(early \mid car, 0) \cdot P(fast \mid 0) \\ &\quad + P(yes \mid early, slow) \cdot P(early \mid car, 0) \cdot P(slow \mid 0) \\ &\quad + P(yes \mid late, fast) \cdot P(late \mid car, 0) \cdot P(fast \mid 0) \\ &\quad + P(yes \mid late, slow) \cdot P(late \mid car, 0) \cdot P(fast \mid 0) \\ &= (0.95 \cdot 0.75 \cdot 0.9) + (0.7 \cdot 0.75 \cdot [1 - 0.9]) + (0.7 \cdot [1 - 0.75] \cdot 0.9) \\ &\quad + (0.35 \cdot [1 - 0.75] \cdot [1 - 0.9]) \\ &= 0.6375 + 0.0525 + 0.1575 + 0.00875 \\ &= 0.85625 \end{aligned}$$

0.5 $M = car, N = 1$

$$\begin{aligned} P(yes \mid 1, car) &= P(yes \mid early, fast) \cdot P(early \mid car, 1) \cdot P(fast \mid 1) \\ &\quad + P(yes \mid early, slow) \cdot P(early \mid car, 1) \cdot P(slow \mid 1) \\ &\quad + P(yes \mid late, fast) \cdot P(late \mid car, 1) \cdot P(fast \mid 1) \\ &\quad + P(yes \mid late, slow) \cdot P(late \mid car, 1) \cdot P(fast \mid 1) \\ &= (0.95 \cdot 0.75 \cdot 0.8) + (0.7 \cdot 0.75 \cdot [1 - 0.8]) + (0.7 \cdot [1 - 0.75] \cdot 0.8) \\ &\quad + (0.35 \cdot [1 - 0.75] \cdot [1 - 0.8]) \\ &= 0.57 + 0.105 + 0.14 + 0.0175 \\ &= 0.8325 \end{aligned}$$

0.6 $M = car, N = 2$

$$\begin{aligned} P(yes \mid 2, car) &= P(yes \mid early, fast) \cdot P(early \mid car, 2) \cdot P(fast \mid 2) \\ &\quad + P(yes \mid early, slow) \cdot P(early \mid car, 2) \cdot P(slow \mid 2) \\ &\quad + P(yes \mid late, fast) \cdot P(late \mid car, 2) \cdot P(fast \mid 2) \\ &\quad + P(yes \mid late, slow) \cdot P(late \mid car, 2) \cdot P(fast \mid 2) \\ &= (0.95 \cdot 0.75 \cdot 0.7) + (0.7 \cdot 0.75 \cdot [1 - 0.7]) + (0.7 \cdot [1 - 0.75] \cdot 0.7) \\ &\quad + (0.35 \cdot [1 - 0.75] \cdot [1 - 0.7]) \\ &= 0.49875 + 0.1575 + 0.1225 + 0.02625 \\ &= 0.805 \end{aligned}$$

(b) Maximize chance to making the flight

Based on all 6 possibilities calculated above, it seems that choosing to go to the airport by **train** and bring **0 bags** will produce the maximized change of making the flight: 89.9%.