

Rules of Probability

- Definition of conditional probability: $P(A | B) = P(A, B) / P(B)$
- Product rule: $P(A, B) = P(A | B)P(B) = P(B | A)P(A)$
 - Bayes' rule: $P(A | B) = P(B | A)P(A) / P(B)$
- Chain rule: $P(A, B, C) = P(A | B, C)P(B, C) = P(A | B, C)P(B | C)P(C)$
- $P(A \text{ or } B) = P(A \vee B) = P(A) + P(B) - P(A, B)$
- $P(\sim A) = 1 - P(A)$
- Marginalization, or summing out: $P(Y) = \sum_z P(Y, Z = z) = \sum_z P(Y, z)$
- Conditioning, or law of total probability: $P(Y) = \sum_z P(Y, z) = \sum_z P(Y | z)P(z)$
 - Example for binary rvs: $P(a) = P(a, b) + P(a, \sim b) = P(a | b)P(b) + P(a | \sim b)P(\sim b)$
- General inference in a full joint probability distribution: Given we want to find a probability distribution for rv X, given the values (e) of evidence variables E, and Y represents the remaining unknown variables.

$$P(\mathbf{X} | e) = \alpha \cdot P(\mathbf{X}, e) = \alpha \sum_{y \in Y} P(\mathbf{X}, e, y)$$

- If X and Y are (marginally) independent, then
 $P(X, Y) = P(X)P(Y)$ and $P(X | Y) = P(X)$ and $P(Y | X) = P(Y)$
- If X and Y are conditionally independent given Z, then
 $P(X, Y | Z) = P(X | Z)P(Y | Z)$ and $P(X | Y, Z) = P(X | Z)$ and $P(Y | X, Z) = P(Y | Z)$

| | toothache | | -toothache | |
|---------|-----------|--------|------------|--------|
| | catch | -catch | catch | -catch |
| cavity | 0.108 | 0.012 | 0.072 | 0.008 |
| -cavity | 0.016 | 0.064 | 0.144 | 0.576 |