

Uncertainty – probability

$P(A)$ – marginal probability, formally $P(A = a)$

$P(A, B)$ - joint probability, formally $P(A = a, B = b)$, $P(A) \geq P(A, B)$

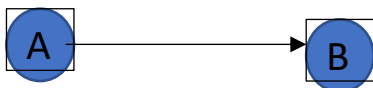
$P(A|B)$ – conditional probability, given B, what is the probability of A,
 $P(A|B) \geq P(A, B)$, but we don't know $P(A)$, $P(B)$, $P(A|B)$

$P(A, B) = P(A|B) P(B) = P(B|A) P(A)$ **Bayes Rule**

Bayesian Network

Why? A way to simplify the storage or computation (training) when we have lots of variables (events) involved through graph models. Assuming each variable has 3 possible values, there are $P(A, \dots, I)$ has power(3, 9) combinations.

A	B	C	D	E	F	G	H	I
0	0	0						
1	0							
2	0							



The arrow edge indicates the causal relationship

Both of the two terms $P(A|B)$ and $P(B|A)$ are valid!

During training stage, most of the time $P(B|A)$ is more convenient to obtain.

For example, A is a season variables {0, 1, 2, 3}, B is a weather variable {0, 1, 2}

$P(B|A)$ is easier to be trained, e.g. when $A = 0$, which is Spring season, then you can train how many days of rain, sun shine, and wind. But $P(A|B)$ can be still valid, especially during testing stage. $P(B|A) * P(A) = P(A|B) * P(B)$

If variables B and E are independent from each other, their joint probability

$P(B, E) = P(B) P(E)$ - factorization (decompose the large joint table into multiple products format)

If variables B and E are not independent: $P(B, E) = P(B)P(E|B) = P(E)P(B|E)$