



Fundamentals of Probability

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Independence

$$\forall x \in \mathbf{x}, y \in \mathbf{y}, p(\mathbf{x} = x, \mathbf{y} = y) = p(\mathbf{x} = x)p(\mathbf{y} = y)$$

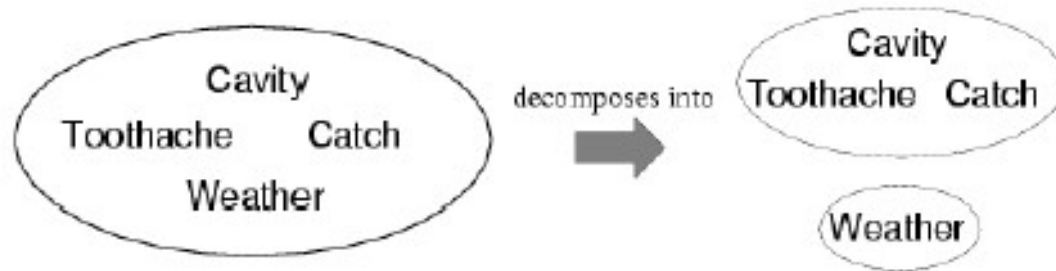
Two events are **independent**, **statistically independent**, or **stochastically independent** if occurrence of one does not affect probability of occurrence of the other

Similarly, two random variables are independent ***if*** realization of one does not affect probability distribution of other

(Absolute) Independence

A and B are independent iff (Note: following are equivalent)

$$P(A|B) = P(A) \quad \text{or} \quad P(B|A) = P(B) \quad \text{or} \quad P(A, B) = P(A) P(B)$$



$$P(\textit{Toothache}, \textit{Catch}, \textit{Cavity}, \textit{Weather}) \\ = P(\textit{Toothache}, \textit{Catch}, \textit{Cavity}) P(\textit{Weather})$$

32 ($2^3 * 4$ (*Weather*)) entries reduced to 12 ($2^3 + 4$ (*Weather*))

Absolute independence is powerful, but rare.

**For your
review!**

Conditional Independence

$$\forall x \in \mathbf{x}, y \in \mathbf{y}, z \in \mathbf{z}, p(x = x, y = y \mid z = z) = p(x = x \mid z = z)p(y = y \mid z = z)$$

Two events x and y are **conditionally independent** given a third event z if occurrence of x *and* occurrence of y are independent events in their conditional probability distribution given z

In other words, x and y are conditionally independent given z if and only if (**iff**), given knowledge that z occurs, knowledge of whether x occurs provides no information on likelihood of y occurring, and knowledge of whether y occurs provides no information on likelihood of x occurring

Conditional Independence

If I have a cavity, probability the probe catches doesn't depend on whether I have a toothache:

$$(1) \mathbf{P}(\text{catch} \mid \text{toothache}, \text{cavity}) = \mathbf{P}(\text{catch} \mid \text{cavity})$$

The same independence holds if I haven't got a cavity:

$$(2) \mathbf{P}(\text{catch} \mid \text{toothache}, \neg \text{cavity}) = \mathbf{P}(\text{catch} \mid \neg \text{cavity})$$

Catch is **conditionally independent** of *Toothache* given *Cavity*:

$$(3) \mathbf{P}(\text{Toothache}, \text{Catch} \mid \text{Cavity}) = \mathbf{P}(\text{Toothache} \mid \text{Cavity}) \mathbf{P}(\text{Catch} \mid \text{Cavity})$$

Equivalent statements:

$$\mathbf{P}(\text{Toothache} \mid \text{Catch}, \text{Cavity}) = \mathbf{P}(\text{Toothache} \mid \text{Cavity})$$

$$\mathbf{P}(\text{Catch} \mid \text{Toothache}, \text{Cavity}) = \mathbf{P}(\text{Catch} \mid \text{Cavity})$$

**For your
review!**

Conditional independence

We can now write out the full joint distribution as:

$$\begin{aligned} & \mathbf{P}(\textit{Toothache}, \textit{Catch}, \textit{Cavity}) \\ &= \mathbf{P}(\textit{Toothache}, \textit{Catch} \mid \textit{Cavity}) \mathbf{P}(\textit{Cavity}) \quad // \textit{product rule} \\ &= \mathbf{P}(\textit{Toothache} \mid \textit{Cavity}) \mathbf{P}(\textit{Catch} \mid \textit{Cavity}) \mathbf{P}(\textit{Cavity}) \quad // \textit{cond. ind.} \end{aligned}$$

In many cases

Use of conditional independence reduces the size of the representation of the joint distribution from exponential in n to linear in n

Conditional independence

Our most basic and robust form of knowledge about uncertain environments

**For your
review!**

Bayes, in English Please?

- What does Bayes' Formula helps to find?
- Helps us to find:

$$P(B | A)$$

- By having already known:

$$P(A | B)$$

$$P(x | y) = \frac{P(x)P(y | x)}{P(y)}$$



Thomas Bayes, 1701-1761

Bayes, in English Please?

- What does Bayes' Formula helps to find?
- Helps us to find:

$$P(B | A)$$

Bayes Theorem shall return!

$$P(x) = \frac{P(x)P(y | x)}{P(y)}$$

- By having already known:

$$P(A | B)$$



Thomas Bayes, 1701-1761

Bayes' Rule

Product rule: $P(a \wedge b) = P(a | b) P(b) = P(b | a) P(a)$

\Rightarrow Bayes' rule: $P(a | b) = P(b | a) P(a) / P(b)$

or in distribution form

$$P(Y|X) = P(X|Y) P(Y) / P(X) = \alpha P(X|Y) P(Y)$$

Causal Probability (useful for diagnostics):

$P(\text{Cause} | \text{Effect}) = P(\text{Effect} | \text{Cause}) P(\text{Cause}) / P(\text{Effect})$

E.g., let M be meningitis, S be stiff neck:

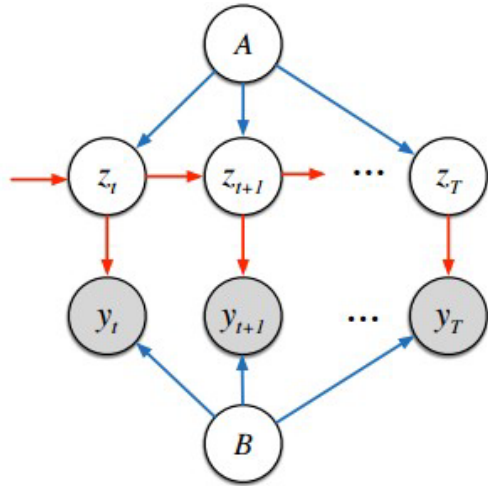
$$P(m|s) = P(s|m) P(m) / P(s) = 0.8 \times 0.0001 / 0.1 = 0.0008$$

Note: posterior probability of meningitis still very small!

Summary of Probability

- Probability is rigorous formalism for *uncertain* knowledge
- Joint probability distribution specifies probability of every atomic event (in sample/event space)
- *Queries* can be answered by summing over atomic events
- For nontrivial domains, we must find ways to reduce joint probability distributional search space
 - *Independence & conditional independence* = your tools for reducing joint probability distribution table size
- **Note:** These ideas/axioms apply equally well to vector/matrix variables

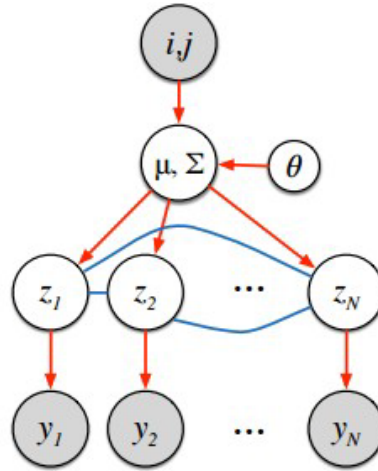
Probability allows us to build models of stochastic, data-generating processes....



**Gaussian Linear State Space Model
Kalman Filter**

$$z_t \sim \mathcal{N}(z_t | Az_{t-1}, \sigma_z^2 I)$$

$$y_t \sim \mathcal{N}(y_t | Bz_t, \sigma_y^2 I)$$

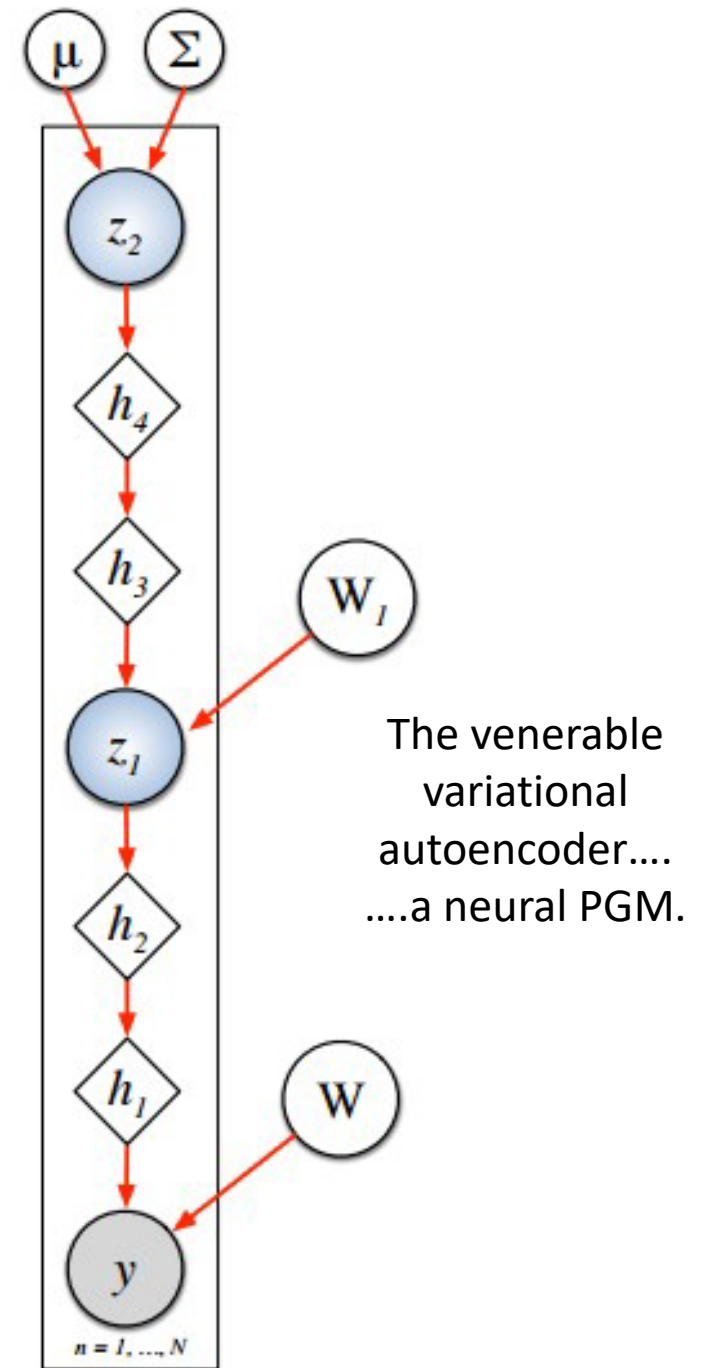


Latent Gaussian Cox Point Process

$$x \sim \mathcal{N}(x | \mu(i, j), \Sigma(i, j))$$

$$y_{ij} \sim \mathcal{P}(c \exp(x_{ij}))$$

Probabilistic graphical models (PGMs)



The venerable
variational
autoencoder....
....a neural PGM.

QUESTIONS?

Deep robots!

Deep questions?!

