

# Probabilistic Graphical Models

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# Chapter 1

## Representation

### 1.1 Introduction

Model

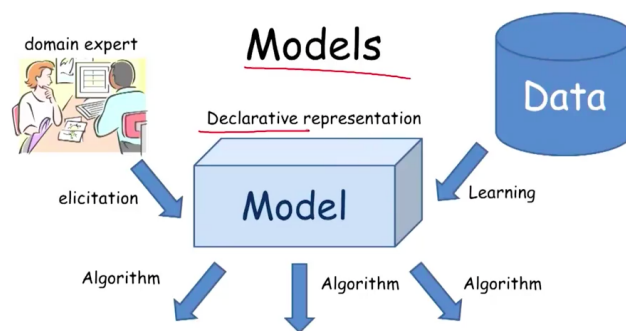


Figure 1.1: Model is a declarative representation of our understanding of the world

It is important because the same representation, that same model can be used in the the context of one algorithms that might answer different kind of questions. Or the same question in more efficient way.

We can construct methodologies the elicit these models from a human expert, or learn from data or combination.

Uncertainty

- Partial knowledges of state of the world
- Noisy observations
- Phenomena not covered by our model
- Inherent stochasticity

Probability Theory

- Declarative representation with clear semantics
- Powerful reasoning patterns: conditioning decision making

- Established learning methods
- Complex Systems
- Graphical Models: Bayesian Networks, Markov Networks (directed or undirected graphs)
- Graphical Representation
  - Intuitive and compact data structure
  - Efficient reasoning using general purpose algorithms
  - Sparse parameterization
  - feasible elicitation : by hand
  - learning from data automatically

### 1.1.1 Distribution

Joint Distribution:  $P(I, D, G)$

Conditioning: observation 1 value of variable  $\rightarrow$  Reduction  $\rightarrow$  Renormalization  $P(I, D, g^1) \rightarrow P(I, D | g^1)$

Marginalization:  $\sum_I P(I, D) = P(D)$  . Example: you have thrown two 6-sided dice,  $D_1$  and  $D_2$ .  $P(D_1, D_2)$  is a joint probability distribution. The probability that  $D_2 = 1$  is equals to  $\sum_{i=1}^6 P(D_1 = i, D_2 = 1)$ .

### 1.1.2 Factors

A factor is a function or table  $\phi(X_1, \dots, X_k)$

$\phi : Val(X_1, \dots, X_k) \rightarrow R$

Scope =  $X_1, \dots, X_k$

Joint distribution is a factor

Unnormalized measure is a factor

Conditional Probability Distribution (CPD) is a factor  $P(G|I, D)$ :  $G$  in columns while  $I, D$  in rows.

Why factors?

- Fundamental building block for defining distributions in high-dimensional spaces
- Set of basic operations for manipulating these probability distributions

## 1.2 Bayesian Network (Directed Models)

### 1.2.1 Semantics and Factorization

What does random variable depend on?

Draw nodes, edges, each node with a factor is CPD (conditional probability distribution)

A bayesian network is:

- A directed acyclic graph (DAG)  $G$  whose nodes represent the random variables
- For each node  $X_i$  a CPD  $P(X_i | Par_G(X_i))$

The BN represent a joint distribution via the chain rule for Bayesian Networks

$$P(X_1, \dots, X_n) = \prod_i P(X_i | \text{Par}_G(X_i))$$

BN is a Legal distribution :  $\sum P = 1$  and  $P > 0$

### 1.2.2 Reasoning Pattern

Causal Reasoning: reasoning going down

Evidential Reasoning: reasoning going up

Inter-causal Reasoning: The probability of class is hard, if we observe the "C" grade and change the posterior probability of high intelligence is goes up