



# Graphical Models: Bayesian Networks

# Objectives



Objective

Describe Bayesian  
Networks



Objective

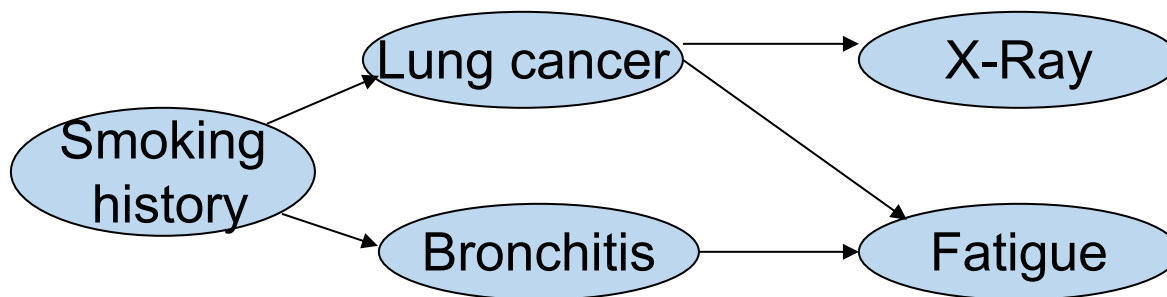
Illustrate key tasks  
in implementing  
Bayesian Networks

# Why do we use graphical models?

| In machine learning, we are often concerned with joint distributions of many random variables.

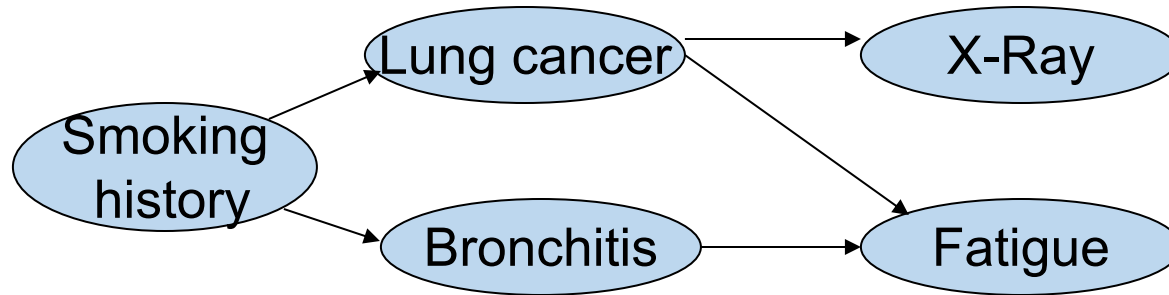
| A graph may provide an intuitive way of representing or visualizing the relationships of the variables.

- Making it easier for domain experts to build a model



# Graphical models for Causal Relations

| Graphical models arise naturally from, often causal, independency relations of physical events.

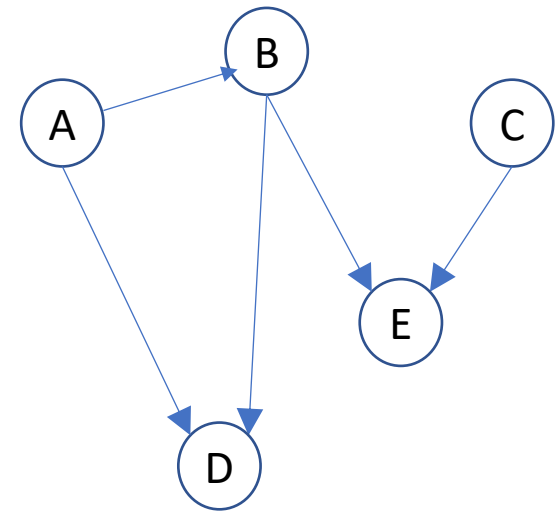


| Caveat: probabilistic relationship does not imply causality.

# Bayesian Networks

| A BN is directed acyclic graph (DAG), where

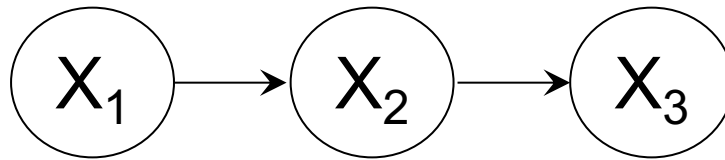
- Nodes (vertices) represent random variables.
- Directed edges represent immediate dependence of nodes.



| Other names: Belief networks, Bayes nets, etc.

# Conditional Independence

| E.g., given the following graph, check the relationship between  $X_3$  and  $X_1$



- $X_3$  is dependent of  $X_2$ , and  $X_2$  is dependent of  $X_1$
- Thus  $X_3$  is dependent of  $X_1$
- But given  $X_2$ ,  $X_3$  is dependent of  $X_1$

➔ Conditional Independence

# BN for General Conditional Dependency

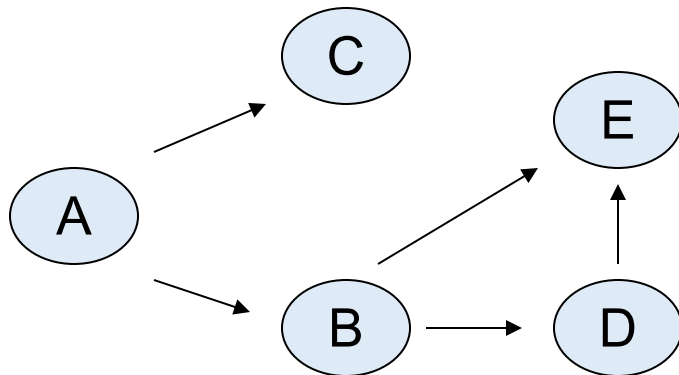
| A BN can be used to model given conditional dependencies

– For example, using the *chain rule of probability*, we have

$$P(A,B,C,D,E)=P(A)P(B|A)P(C|A,B)P(D|A,B,C)P(E|A,B,C,D)$$

| If we know that, given A, C won't rely on B, and so forth, we may have

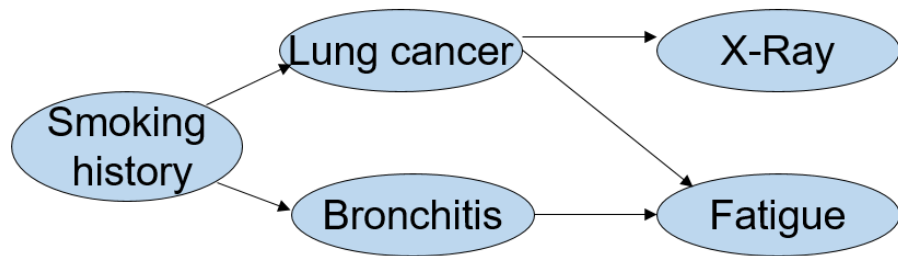
$$P(A,B,C,D,E)=P(A)P(B|A)P(C|A)P(D|B)P(E|B,D)$$



➤ We could represent joint distributions more compactly in BN → Efficient computation

# Inference in Bayesian Networks

| Given a model and some data (“evidence”), how to update our belief?

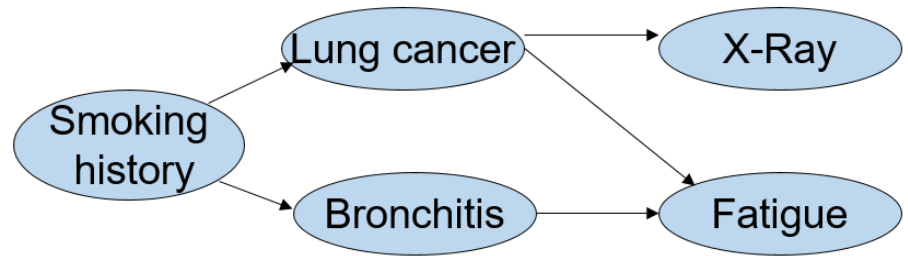


← What are the model parameters?



# Inference in Bayesian Networks (cont'd)

| Given a model and some data (“evidence”), how to update our belief?

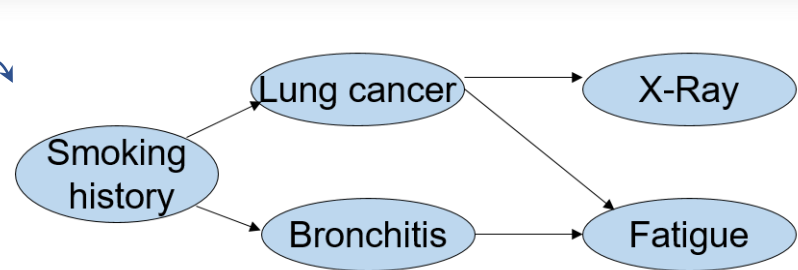


❖ E.g., for a patient with certain smoking history (non-smoker), whose X-ray result is positive, and who does not experience fatigue:

❖ What is probability of having lung cancer?

# Inference in Bayesian Networks (cont'd)

| In a simple BN like this, we can compute the exact probabilities.



| In general, for a tree-structured BN, we may use **belief propagation** for the inference problem.

| For general structures, sometimes it is possible to generalize the above method (e.g., the *junction tree algorithm*). More often, we must resort to approximation methods

- E.g. Variational methods, Sampling (Monte Carlo) methods.

# Learning in Bayesian Networks



- | Learning parameters (probabilities) for a given BN (the graph is given).
  - Estimate the (conditional) probabilities from past data.
- | Learning both the structure and the parameters for a BN
  - A more challenging task beyond the scope of this discussion.

# Learning the Probabilities

## | Basic ideas

- Use relative frequency for estimating probability.
- A prior distribution is typically assumed.
- The prior is then updated by the data into posterior.
- Using the MLE principle

## | The so-called “Expectation-Maximization (EM) Algorithm” is often used.

- Iteratively update our guess for the parameter and each step attempts to apply the MLE principle.