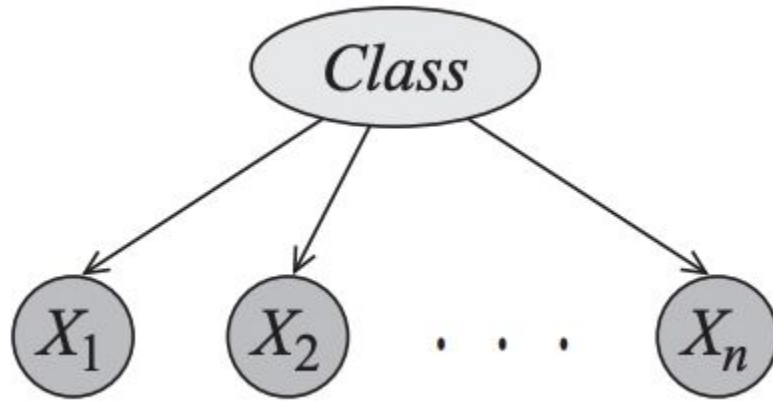


# Advanced Machine Learning

Likhith Nayak

# Naive Bayes Model



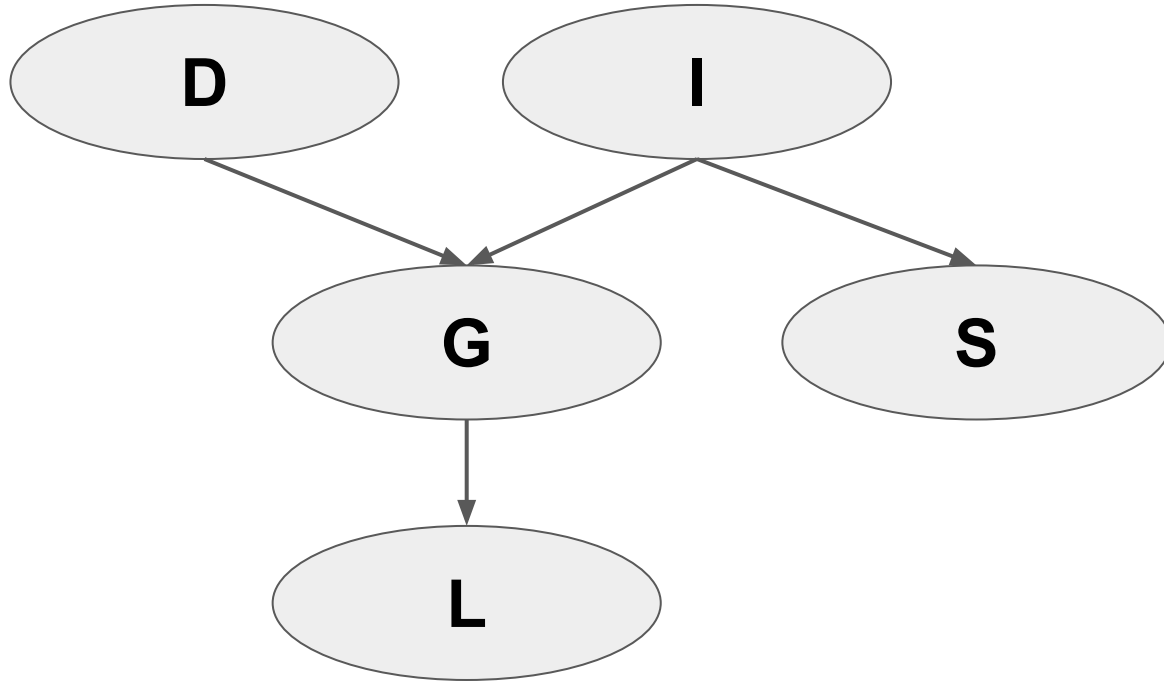
$$P(C, X_1, \dots, X_n) = P(C) \prod_{i=1}^n P(X_i \mid C).$$

# Bayesian Network

A Bayesian network structure  $\mathcal{G}$  is a *directed acyclic graph* whose *nodes represent random variables*  $X_1, \dots, X_n$ . Let  $\text{Pa}_{X_i}^{\mathcal{G}}$  denote the parents of  $X_i$  in  $\mathcal{G}$ , and  $\text{NonDescendants}_{X_i}$  denote the variables in the graph that are not descendants of  $X_i$ . Then  $\mathcal{G}$  encodes the following set of conditional independence assumptions, called the *local independencies*, and denoted by  $\mathcal{I}_{\ell}(\mathcal{G})$ :

*For each variable  $X_i$ :  $(X_i \perp \text{NonDescendants}_{X_i} \mid \text{Pa}_{X_i}^{\mathcal{G}})$ .*

# Bayesian Network



$$(L \perp I, D, S \mid G)$$

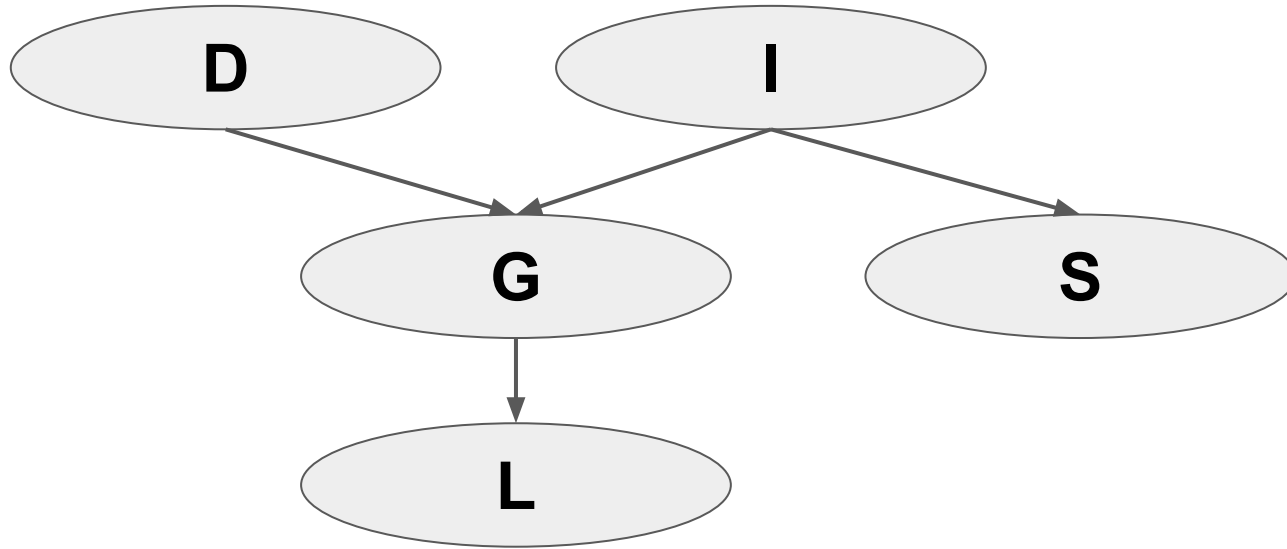
$$(S \perp D, G, L \mid I)$$

$$(G \perp S \mid I, D)$$

$$(I \perp D)$$

$$(D \perp I, S)$$

# Bayesian Network



$$P(I, D, G, L, S) = P(I)P(D | I)P(G | I, D)P(L | I, D, G)P(S | I, D, G, L)$$

# Bayesian Network (BN)

*Let  $\mathcal{G}$  be a BN graph over the variables  $X_1, \dots, X_n$ . We say that a distribution  $P$  over the same space factorizes according to  $\mathcal{G}$  if  $P$  can be expressed as a product*

$$P(X_1, \dots, X_n) = \prod_{i=1}^n P(X_i \mid \text{Pa}_{X_i}^{\mathcal{G}})$$

*This equation is called the chain rule for Bayesian networks. The individual factors  $P(X_i \mid \text{Pa}_{X_i}^{\mathcal{G}})$  are called conditional probability distributions (CPDs) or local probabilistic models.*

# Independencies in Bayesian Networks



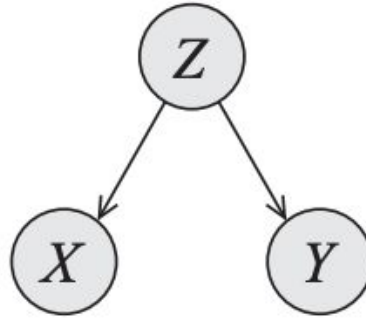
(a)

$$X \perp Y \mid Z$$



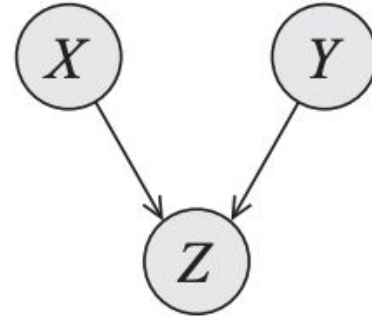
(b)

$$X \perp Y \mid Z$$



(c)

$$X \perp Y \mid Z$$



(d)

$$X \perp Y$$

# References

Koller, Daphne, and Nir Friedman. Probabilistic graphical models: principles and techniques. MIT press, 2009.