## **Indian Institute of Technology Kanpur**

# National Programme on Technology Enhanced Learning (NPTEL)

# Deep Learning - Part II

Module 16.9 - Bayesian Networks: Formal Semantics

(Refer Slide Time: 00:13)

Deep Learning - Part - II

Module 16.9 - Bayesian Networks: Formal Semantics





Okay, so now having done these three rules through some examples, now I'll formally define the semantics of a Bayesian network and it will just be one single rule which encompasses all of this, okay, so let's look at this.

So Bayesian network is a directed a cyclic graph, there are no cycles in this graph, when nodes represent the random variables X1 to XN, and let P of XI in this graph or PA of XI in this graph denote the parents of XI in G, okay,

(Refer Slide Time: 00:47)

We are now ready to formally define the semantics of a Bayesian Network

### Bayesian Network Semantics:

A Bayesian Network structure G is a directed acyclic graph where nodes represent random variables  $X_1, X_2, ..., X_n$ . Let  $P_{a_{X_i}}^G$  denote the parents of  $X_i$  in G







so PA of XI is all the parents of XI.

And non-descendants of XI denote the variables in the graph that are not descendants of XI, (Refer Slide Time: 00:59)

We are now ready to formally define the semantics of a Bayesian Network

### Bayesian Network Semantics:

A Bayesian Network structure G is a directed acyclic graph where nodes represent random variables  $X_1, X_2, ..., X_n$ . Let  $P_{a_{X_i}}^G$  denote the parents of  $X_i$  in G and NonDescendants $(X_i)$  denote the variables in the graph that are not descendants of  $X_i$ . Then G encodes the following set of conditional independence assumptions called the local independencies and denoted by  $I_i(G)$  for each variable  $X_i$ .





then G encodes a set of independence relations or assumptions for every variable in the graph, for all these XI's, can you give me that rule in a single sentence, in a single expression which encompasses all the rules that we have seen so far, so I'm looking for rules of the form XI is independent of all the way down here, the entire sub tree, XI is independent.

So remember we are interested in independence, when I say I want to know independences I want to know the following, is X independent of Y? That's the best case, if not as it at least independent given Z, so now I'm saying that the Bayesian network for every node that you have, that means for every random variable that you have it encodes certain independence assumptions and I want you to write these three rules that you're seeing in a single line. XI is independent of non-descendants of XI given parents of XI, does that make sense? (Refer Slide Time: 02:07)

XLY Z

We are now ready to formally define the semantics of a Bayesian Network

#### **Bayesian Network Semantics:**

A Bayesian Network structure G is a directed acyclic graph where nodes represent random variables  $X_1, X_2, ..., X_n$ . Let  $P_{a_{X_i}}^G$  denote the parents of  $X_i$  in G and NonDescendants  $X_i$  denote the variables in the graph that are not descendants of  $X_i$ . Then G encodes the following set of conditional independence assumptions called the local independencies and denoted by  $I_i(G)$  for each variable  $X_i$ .



Does this encompass all the three rules that we have seen? Right, so this is the formal semantics of a Bayesian network, once you have the Bayesian network you can just read off these independences from the Bayesian network, is that fine? Okay, so that's where we will stop here, (Refer Slide Time: 02:23)

 We will see some more formal definitions and then return to the question of independencies.





and we'll continue in the next class.

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