# CS 536 Course Overview

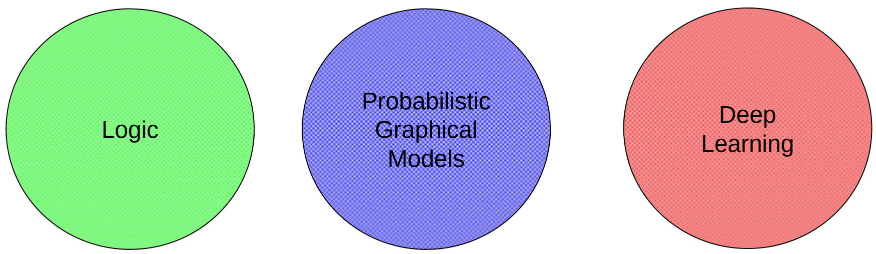


## Introduction

- Probabilistic graphical models encode joint probability distributions as a graph structure
- Why study Bayesian networks?
  - One of the major machine learning approaches
  - Nice framework for building probabilistic models
  - Lots of interesting connections with other areas of AI (e.g. deep learning and logic)

## The Really Big Picture

Three major approaches influencing artificial intelligence over the years:

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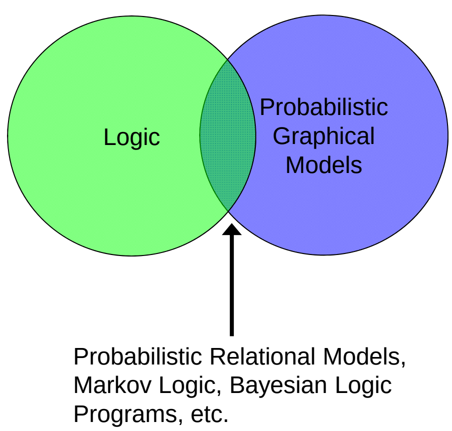
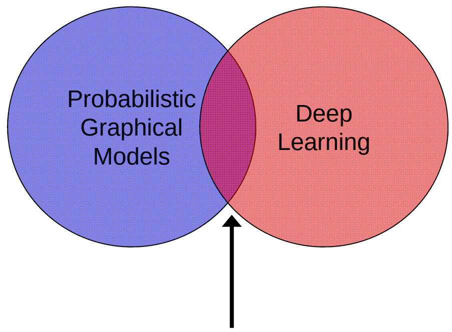
## The Really Big Picture

Probabilistic graphical models overlap with Logic



# The Really Big Picture

And also with deep learning…




Logistic Regression, Restricted Boltzman Machines, Variational Autoencoders, etc.

# Graphical Models and Deep Learning

**Graphical Models**

- Compact representation of a joint probability distribution
- Can incorporate domain knowledge via priors
- The hard part: developing efficient inference algorithms
- May not need as much data as deep learning

**Deep Learning**

- Function approximator: maps inputs to outputs
- Doesn't always represent a probability distribution
- Great for learning representations
- Can be awkward to incorporate domain knowledge
- The hard part: architecture building, hyperparameter tuning
- Needs lots of data

## Introduction

This course is about probabilistic graphical models. Specifically, it covers:

1. Representation
2. Inference
3. Learning
4. Connections with Deep Learning

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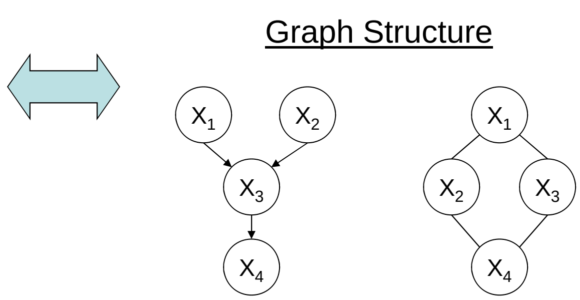
## Representation

Joint Probability Distribution
$P(X_1, \ldots, X_m)$




Directed Graphical Model eg. Bayesian network

Undirected Graphical Model eg. Markov Network

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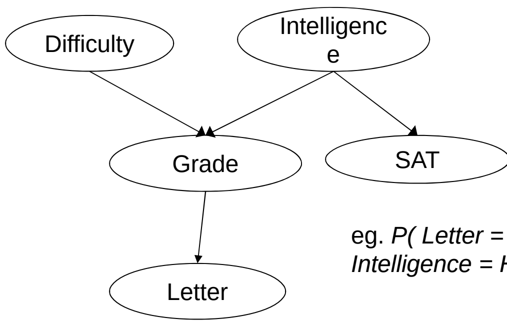
# Inference

Given a graphical model, we would like to compute probabilistic queries of the form *P( **X** | **E**)*




eg. *P( Letter = Strong | Difficulty = High, Intelligence = High)*

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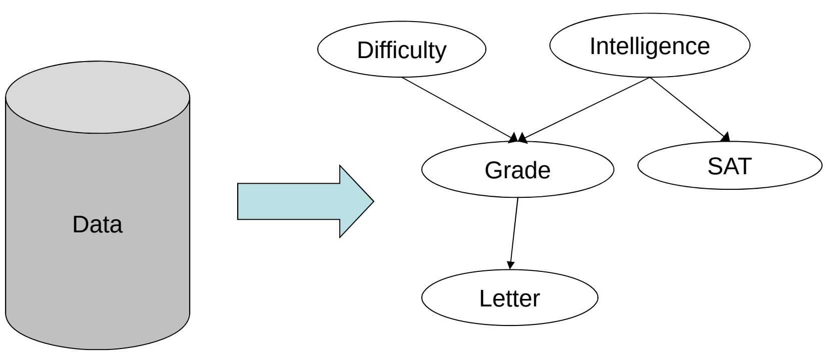
# Learning




How do I learn the structure and/or parameters of a Bayesian network from data?

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## Connections with Deep Learning

Topics include:

- Restricted Boltzmann machines, Deep Boltzmann machines
- Variational inference and Variational Autoencoders
- (If we have time) Sum-Product networks

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## Uses of Bayesian Networks at OSU

- Species Distribution Modelling
- Insider threat detection
- Activity Monitoring
- Intelligent Desktop Assistants
- Real-time strategy games
- Image recognition and segmentation
- Sensor data cleaning
- More on its way!

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## Quick Stats Review

Suppose two random variables $X$ and $Y$ are (marginally) independent of each other. Then:

1. $P(X, Y) = P(X)P(Y)$
2. $P(X|Y) = P(X)$
3. $P(Y|X) = P(Y)$

Suppose two random variables $X$ and $Y$ are conditionally independent of each other given Z. Then:

1. $P(X, Y|Z) = P(X|Z)P(Y|Z)$
2. $P(X|Y, Z) = P(X|Z)$
3. $P(Y|X, Z) = P(Y|Z)$

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## Quick Stats Review

Chain rule of probability:

$$P(X, Y) = P(X|Y)P(Y)$$

Bayes rule:

$$P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)}$$

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