UNIT 3: Probabilistic Reasoning

Probability, conditional probability, Bayes Rule, Bayesian Networks- representation, construction and inference, temporal model, hidden Markov model.

Understanding Deterministic and Stochastic Models

In the world of modeling and simulations, two primary types of models are used to predict outcomes: **deterministic** and **stochastic** models. Each serves distinct purposes and offers advantages depending on the system being modeled and the type of predictions required.

Deterministic Models

What Are They?

- **Deterministic models** consistently produce the **same outcome** for given initial conditions, operating under fixed rules without randomness.

Characteristics:

- **Predictable Results**: Yields no uncertainty in outcomes. Given the same initial data, the result will always be identical.
- **No Probability**: These models do not utilize probabilities or statistical fluctuations.

Common Uses:

- **Engineering Calculations**: Crucial for designs where exact outcomes are necessary, such as in constructing buildings or manufacturing precise machinery.
- **Physical Sciences**: Useful in modeling scenarios where physical laws apply strictly, such as the orbits of planets or electrical circuits.

Pros:

- **Simplicity and Clarity**: Simpler to understand, build, and validate.
- **Precision and Reliability**: Ideal for scenarios that demand exact predictions.

Cons:

- **Lacks Flexibility**: Not suitable for systems with inherent unpredictability.
- **May Over-Simplify**: Can ignore the complexities of real-world systems that involve random variability.

Stochastic Models

What Are They?

- **Stochastic models** account for randomness and variability. They are designed for systems where the same initial conditions can lead to different outcomes due to inherent uncertainties.

Characteristics:

- **Random Variables**: Incorporate elements of chance, making outcomes less predictable.
- **Probability Distributions**: Employ probabilities to manage the uncertainties within the model.

Common Uses and Examples:

- **Weather Forecasting**: Predicting weather involves numerous unpredictable atmospheric factors.
- **Stock Market Analysis**: Financial markets are influenced by unpredictable economic and social elements.
- **Hidden Markov Models (HMM)**: Used in speech recognition and genetic data analysis where the actual states influencing outputs are not directly observable.
- **Bayesian Networks**: Employed in decision-making processes across various fields, including medicine for diagnostic systems and in AI for probabilistic reasoning and learning.

Pros:

- **Real-World Applicability**: More effective for complex systems where uncertainty or human behavior is a factor.
- **Handles Uncertainty**: Provides a range of possible outcomes, offering a broader perspective on potential scenarios.

Cons:

- **Complexity**: More complicated to design and requires meticulous statistical analysis.
- **Computational Intensity**: Often demands more computational power to perform simulations.

Choosing Between Deterministic and Stochastic Models

Which to Use?

- **Deterministic models** are best when outcomes need to be precise and the system's behavior is well-understood under controlled conditions.
- **Stochastic models** are preferred for dealing with complex realities where uncertainty is a significant factor, such as in biological or economic systems.

Both models serve as vital tools for understanding and predicting system behaviors. The choice of model depends on the project's specific needs, including the level of uncertainty and the nature of the available data.

Conclusion

Deterministic and **stochastic models** are foundational in data analysis, system prediction, and design. Knowing when to use each can help researchers and engineers provide accurate insights and reliable forecasts tailored to their specific requirements.

Bayesian Networks- Representation, Construction and Inference,

A Bayesian Network is like a map of causes and effects, showing how different things (called variables) are connected by probabilities. It helps us understand and update our beliefs when we get new information.

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1. Representation

1. **Nodes**: Each circle (node) is something we care about, like “Rain” or “Traffic.”
2. **Arrows**: An arrow from “Rain” to “Traffic” means **Rain can affect Traffic**.
3. **Probability Tables**: Each node has a small table that says:
    - “If my parent node is true or false, how likely am I to be true or false?”

Example:

- If “Smoking” is true, “Lung Cancer” might be more likely.

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2. Construction

1. **Pick Your Nodes**: Think about all the events or conditions you want to show (e.g., “Rain,” “Traffic Jam,” “Late to Work”).
2. **Draw Arrows**: Connect them where one can **directly influence** the other.
3. **Fill in Probabilities**: For each node, decide: “How likely is it if the parent node is true or false?”

Tip: Use **data** or **expert advice** to figure out these numbers.

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3. Inference

Inference is how you **update** or **find out** new probabilities when you learn something.

- **Learn something** (e.g., “I see a traffic jam”).

- **Update everything** else (e.g., “If there’s a traffic jam, maybe it’s more likely raining”).

This is done by **calculating** with the probabilities in the network.

Why Use Bayesian Networks?

- They show how **things connect** and **how likely** they are.
- They handle **uncertain situations** in a **clear** way.
- They let you **change** what you think when you **learn new information**.

Summary

A Bayesian Network is a **graph** of connected **events** with **probabilities**. You **draw** it by linking what can **cause or affect** something else. You **fill in** how likely each event is. Then you **update** or **figure out** probabilities when you get **new evidence** (like seeing a traffic jam).

Note: For example go with the same problem we have solved in class

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Asian Bayesian Network Example:[https://www.bayesserver.com/examples/networks/asia (https://www.bayesserver.com/examples/networks/asia)](https://www.bayesserver.com/examples/networks/asia)

Asia Network

The **Asia Network** is a simple **Bayesian network** often used to teach how **probabilistic models** work. It shows **how certain health conditions (like tuberculosis or lung cancer)** and factors like **smoking** or a **visit to Asia** can affect a person’s risk of diseases, symptoms, and test results.

Key Nodes (Variables)

1. **Visit to Asia (A)**- Whether the patient has traveled to Asia (increases risk of tuberculosis).
2. **Tuberculosis (T)**- Whether the patient has tuberculosis. Depends on the **visit to Asia**.
3. **Smoking (S)**- Whether the patient smokes. Raises risk for **lung cancer** and **bronchitis**.
4. **Lung Cancer (L)**- Whether the patient has lung cancer. Depends on **smoking**.
5. **Bronchitis (B)**- Whether the patient has bronchitis. Also depends on **smoking**.
6. **Tuberculosis or Cancer (E)**- Indicates if the patient has **tuberculosis, lung cancer, or both**.
7. **X-ray Result (X)**- Shows if a chest X-ray is **abnormal**. Likely abnormal if **tuberculosis or lung cancer** is present.
8. **Dyspnea (D)**- Whether the patient has **shortness of breath**. Caused by **tuberculosis, lung cancer, or bronchitis**.

How It Works

Each node has a **conditional probability table (CPT)** showing how likely it is, **given its parent nodes**. For instance:

- **P(T | A)**: Probability of tuberculosis given whether the patient visited Asia.
- **P(L | S)**: Probability of lung cancer given smoking status.

These tables let us calculate how a **change** in one variable (like “patient is a smoker”) affects **other** probabilities (like the chance of lung cancer or an abnormal X-ray).

Why It’s Useful

- **Educational**: Simplifies the idea of how **multiple factors** (e.g., travel, smoking, lung issues) can be connected in a **probabilistic** way.
- **Medical Diagnosis**: Real-world Bayesian networks use symptoms, test results, and lifestyle factors to calculate **disease probabilities**.

Examples of Questions It Can Answer

- **“What’s the chance of lung cancer if someone smokes and has an abnormal X-ray?”**

- **“How much does traveling to Asia increase the risk of tuberculosis?”**

By using **Bayesian inference**, the Asia network can **update** these probabilities when we learn new evidence (like a patient’s X-ray result).

Conclusion

The **Asia Network** is a classic, **small** Bayesian network showing **how a few factors** (smoking, travel) can lead to **various diseases and symptoms**. It’s a **great teaching tool** for understanding **probabilistic reasoning** and **inference** in medicine and beyond.

Weather Forecasting with Bayesian Networks

What Is a Bayesian Network?

A **Bayesian Network** is a **diagram** that shows how different **factors** (like temperature, humidity) **influence each other** and how **likely** each is to happen.

How It Helps in Weather Forecasting

1. **Nodes (Variables)**
    - Each **circle** (node) in the network is something about the weather, like **Temperature**, **Pressure**, or **Rain**.
2. **Arrows (Connections)**
    - Arrows show which factors **affect** others. For example, **Sea Temperature** might affect **Storm Formation**.
3. **Probabilities**
    - Each node has a **probability table** (CPT) that says:
        - “If X is high, then Y is likely to be...”

Building the Network

1. **Collect Data**
    - **Satellite Images** (cloud cover, sea temps)
    - **Radar** (rain, storms)
    - **Weather Stations** (local temperature, humidity, wind)
    - **Historical Records** (past patterns)
2. **Create Nodes**
    - One node for each **important weather variable** (Temperature, Rain, Wind Speed, etc.).
3. **Link Them**
    - Draw **arrows** showing how one affects another (e.g., “Humidity” → “Rain”).
4. **Assign Probabilities**
    - For each node, fill a **table** showing the chance it takes a certain value depending on its parent nodes.

Using the Network for Forecasts

1. **Simulations**
    - The network can **simulate** weather conditions and calculate how likely certain weather (like heavy rain) is.
2. **Real-Time Updates**
    - New data (like updated radar info) can **update** the network’s predictions on the fly.
3. **Probabilistic Predictions**
    - It doesn’t just say “It will rain”; it says **how likely** the rain is—e.g., “There’s a 70% chance of rain.”
4. **Decision Support**

- These forecasts can help **plan** for severe storms, floods, or other weather events.

Benefits

- **Handles Uncertainty**: Weather is unpredictable, so Bayesian Networks can **adapt** when new information arrives.
- **Combine Different Data**: Use satellite, radar, station data all at once.
- **See How Variables Interact**: It's not a "black box"—the network shows **which factors** influence others.

Challenges

- **Complex Construction**: Requires **expert knowledge** in weather and probabilities.
- **High Computation**: Large networks with many variables can be **expensive** to run, especially in real time.

Conclusion

Bayesian Networks help **forecast weather** by linking key **weather factors** and **updating** predictions when new data comes in. They give **probabilistic** (not just yes/no) forecasts and can **improve accuracy**, making them very useful in meteorology.

Markov Model

A **Markov Model** is a way to describe a system where each **next state** depends only on the **current state**, not on how we got there. This property is called "**memorylessness**."

- **Observable States**: We can **see** each state directly.
- **Transition Probabilities**: These tell us the **chance** of moving from one state to another. Usually shown in a **matrix** (a table of numbers) where each row tells you the probabilities of moving to other states.

Examples:

- **Weather Forecasting**: Each day's weather (sunny, rainy, etc.) depends only on today's weather.
- **Queue Lines**: The chance of a new customer arriving depends on the current situation, not how the line formed.

Hidden Markov Model (HMM)

A **Hidden Markov Model** is like a Markov Model, **but** we **cannot see** the actual states. Instead, each hidden state **emits** something we **can** observe (like a sound or a symbol).

- **Hidden States**: We don't directly see them; we only guess they're there.
- **Observable Emissions**: Each hidden state produces something we **can** measure (e.g., a word, a sound).
- **Transition & Emission Probabilities**:
  - **Transition**: How likely we move from one hidden state to another.
  - **Emission**: How likely a hidden state is to produce a certain visible output.

Examples:

- **Speech Recognition**: We can't see the exact sounds forming in someone's mouth (hidden states), but we hear the **spoken words** (emissions).
- **Biology**: In DNA, hidden states could be protein-coding regions, but we only see the **sequence** of letters (A, T, G, C).

Summary

1. **Markov Model**:
   - **States are visible**.
   - Future depends **only** on the current state.
2. **Hidden Markov Model (HMM)**:
   - **States are hidden**, but they produce visible outputs.

- Must **infer** the hidden states from the outputs.

Both use the idea that "**the future depends only on the present**" (Markov property), but HMMs deal with hidden processes, making them useful when we can’t directly see the underlying states.

Note: For example go with the same problem we have solved in class

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