

SNS COLLEGE OF TECHNOLOGY



An Autonomous Institution
Coimbatore-35

DEPARTMENT OF INFORMATION TECHNOLOGY

23ITT304 Information Coding Technique

Unit I

Information Theory

Joint and Conditional Entropy

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Joint and Conditional Entropy

Understanding Information in Combined and Dependent Events



Icebreaker: How Much Do You Know?

Let's Reflect

- Have you ever compressed a file and wondered how much data was truly 'removed'?
- Can knowing one event help predict another in communication systems?

Think of a real-life example where two events are linked—like rain and traffic delays.

We'll build on these ideas to explore how information theory quantifies uncertainty in connected events.



Session Objectives

By the end of this session, you will:

- Define **joint entropy** and **conditional entropy** in information theory.
- Compute both using probability distributions.
- Understand their role in data compression and communication.
- Apply concepts through real-world examples and group problem-solving.
- Connect entropy to broader applications in AI, cryptography, and machine learning.



Design Thinking: Persona & Problem

1 Empathize

Arjun, a data engineer, needs efficient data compression without losing critical variable relationships.

2 Define

Measuring total uncertainty of two random variables & how one reduces the other's.

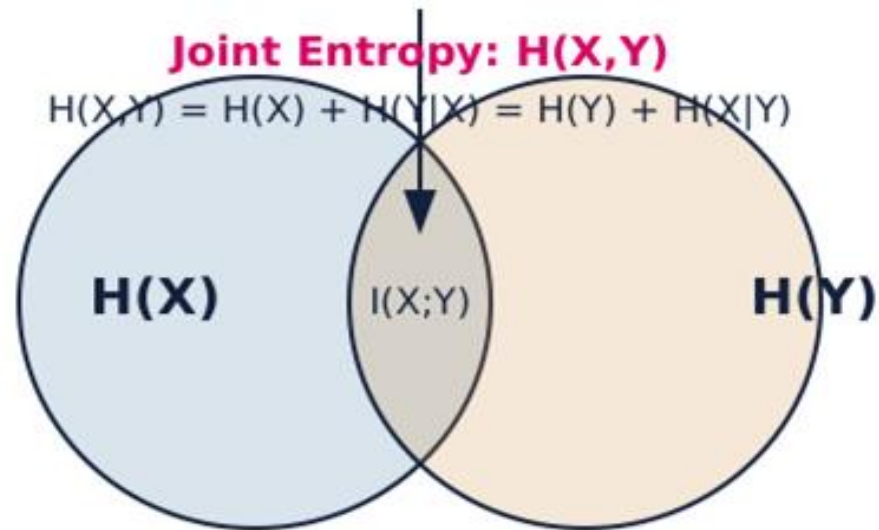
3 Ideate

Joint/conditional entropy models dependencies, optimizes encoding via variable relationships.

4 Prototype

Predict user behavior from login patterns and device usage.

Joint Entropy: Total Uncertainty



Total Uncertainty of both variables

$$H(X,Y) = -\sum_x \sum_y p(x,y) \log_2 p(x,y)$$

Computing Joint Entropy



	Light	Heavy
Sun	0.4	0.1
Rain	0.2	0.3

$p(x,y)$ Joint Probability Table

X	Y
0.4	0.1
...	...



$$H(X,Y) = - \sum$$

$$[0.4 \log_2 0.4 + 0.1 \log_2 0.1 + \dots]$$

Step 1

List all possible outcomes of two variables, like (Weather, Traffic).

Step 2

Build a joint probability table with $p(x,y)$ for each pair.

Step 3

Apply formula: $H(X,Y) = - \sum p(x,y) \log_2 p(x,y)$ over all pairs.

Conditional Entropy: Knowing One, Predicting Another

What Is $H(Y|X)$?

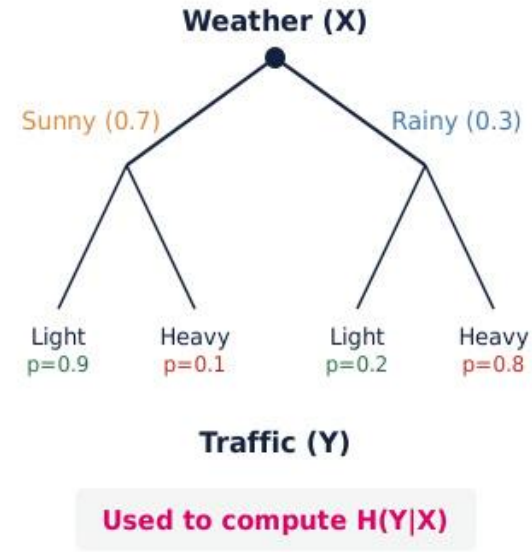
It measures the average uncertainty in Y when X is known.

Formula: $H(Y|X) = \sum p(x) H(Y|X=x)$

Real-World Insight

If knowing the weather reduces uncertainty about traffic, then $H(\text{Traffic}|\text{Weather}) < H(\text{Traffic})$.

This is key in efficient coding—why send full traffic data if weather already tells part of the story?



T-Shaped Learning: Depth & Breadth

Entropy Chain Rule

$$H(X,Y) = H(X) + H(Y|X)$$

| | |
 Joint Marginal Conditional



Vertical Depth

Master entropy formulas, chain rules, and their derivations in information coding.

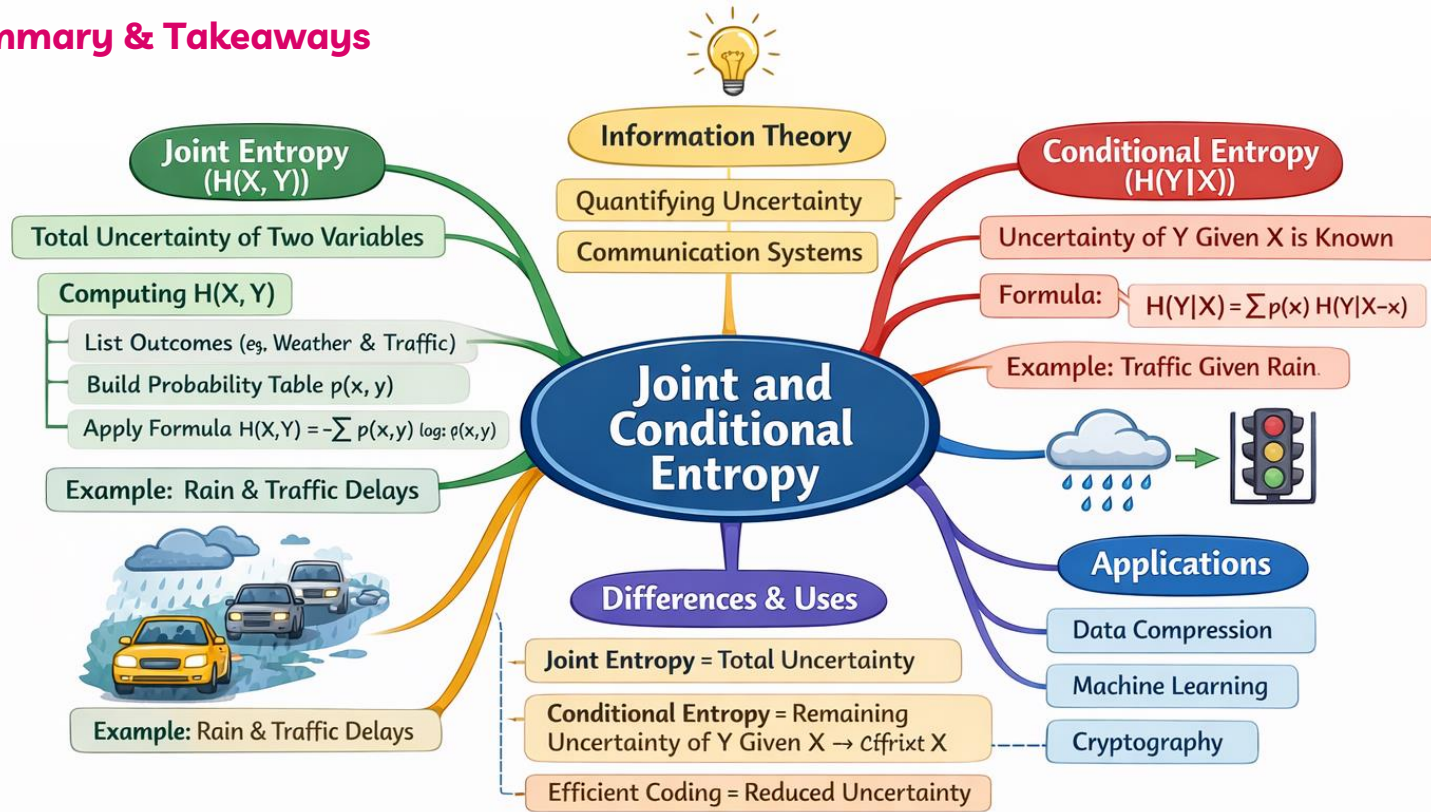
Interdisciplinary Links

Apply to machine learning (feature selection), cryptography (key entropy), and neuroscience (neural coding).

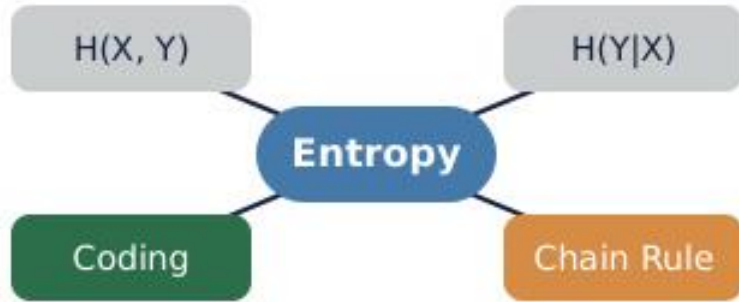
Future Scope

Quantum information theory uses entropy to measure qubit uncertainty and entanglement.

Summary & Takeaways



Summary & Takeaways



Reflect & Share

Discuss: Where have you seen dependent events in your work? How could entropy optimize such systems?

Answer: Can conditional entropy be greater than joint entropy? Why/why not?

Key Concepts

- **Joint Entropy:** Total uncertainty of two variables.
- **Conditional Entropy:** Remaining uncertainty when one is known.
- **Chain Rule:** $H(X,Y) = H(X) + H(Y|X)$

These help design smarter, more efficient codes.



Thank you