Semantics & Pragmatics

Semantics

- **How Humans Handle Semantics — and How We Enable Machines to Do So ?**
- **Human semantic knowledge is multi-modal, contextual, grounded, and experience-driven.**

Human vs Machines

How do humans represent and process meaning?

How can machines approximate this ability?

How do humans represent and process meaning?

Semantic grounding

- **Perception** (shape, color)
- **Action** (eating, cutting)
- **Emotion** (liking)
- **Language** (usage patterns)
- **Memory** (experiences)

Mental Lexicon (Human Semantic Store)

Humans store words in a **semantic network**:

Nodes = concepts

Edges = semantic relations

- *dog* → *animal* → *mammal*
  dog → *bark* → *leash* → *walk*

Core Properties of Human Semantic Processing

- **Compositionality (Meaning Building)**
  - **“Red apple”**
  - Humans compute meaning dynamically:
    - *red* modifies *apple*
    - Visual + conceptual integration
- This scales to:
  - “The boy who was hungry ate the apple slowly.”
- Humans:
  - Track **roles**
  - Track **events**
  - Track **temporal structure**

Cont..

- **Context Sensitivity:**
  - “I went to the bank.”

- Meaning depends on:
  - Previous sentence
  - Topic
  - World knowledge
- Humans resolve ambiguity effortlessly using **contextual prediction**.

Cont..

- **Probabilistic Meaning**

"Humans do not compute meaning deterministically."

- "Birds fly"
  → True in general
  → False for penguins
- Human semantics is:
  - Gradient
  - Probabilistic
  - Exception-tolerant

How the Brain Handles Semantics ?

- Key insights from cognitive neuroscience:
  - No single “semantic area”
  - Distributed cortical representations
  - Strong interaction with perception & motor systems

- **Implication for NLP:**
  - Meaning is **distributed**, not symbolic alone.

Why Classical NLP Failed to Capture Human Semantics ?

- **Early Symbolic Approaches**
  - Dictionaries
  - Rules
  - Logic
- **Problems:**
  - Brittle
  - No grounding
  - No learning
  - No ambiguity tolerance

Machines knew **definitions**, not **meaning**.

Distributional Hypothesis

"You shall know a word by the company it keeps."

- Humans learn meaning from **usage**.
- Machines can do the same.

How Machines Learn Semantics ?

- **Distributional Semantics:**
  Words → vectors
  Meaning → geometry

- Properties:
  - Similar meaning → nearby vectors
  - Relations → vector arithmetic
- This mirrors:
  - Human associative networks
  - Semantic similarity judgments

Contextual Semantics (Transformer Revolution)

Humans interpret meaning **in context**.

Transformers do the same.

Example:

- “The **bank** was crowded.”
- Model attention captures:
    - Surrounding words
    - Discourse context
    - Task objective
- This enables:
    - Dynamic meaning
    - Disambiguation
    - Role sensitivity

Meaning as Prediction

Humans constantly predict:

- Next word
- Speaker intent
- Event outcome

Transformers learn semantics by:

Predicting what comes next

This aligns with:

- Predictive coding theories of the brain
- Statistical learning in humans

Machines **simulate** understanding, not **experience** it.

What Machines Still Lack Compared to Humans

Human Semantics	Machine Semantics
Grounded in perception	Mostly text-only
Experience-based	Data-driven
Intent-aware	Pattern-based
Self-correcting	Can hallucinate

How Humans Handle Pragmatics — and How We Enable Machines to Do So ?

If someone says, "It's very hot in here," what do they really mean?

Possible interpretations:

- A statement about temperature
- A **request to open a window**
- A complaint
- A hint

This gap between **what is said** and **what is meant** is **PRAGMATICS**.

What Is Pragmatics?

- **Pragmatics = meaning in use**
- Humans do **not** interpret language literally. They interpret language by inferring:
  - Speaker **intent**
  - Listener **beliefs**
  - Shared **context**
  - Social **norms**
  - World **knowledge**
- Humans treat language as **action**, not just information.

Core Cognitive Mechanisms Behind Human Pragmatics

Theory of Mind (ToM)

Humans constantly reason:

“What does the speaker know that I know?”

Example:

“You left the lights on.”

Literal meaning: **statement**

Pragmatic meaning: **request / reproach**

Humans infer:

- Intention
- Expectation
- Social consequence

Shared Context & Common Ground

Humans rely on **common ground**:

- Physical context
- Conversational history
- Cultural norms

“Put it there.”

Requires:

- What is *it*?
- Where is *there*?
- Why *now*?

Machines struggle here because context is **implicit**, not explicit.

Conversational Cooperation

Humans assume speakers are **cooperative**, not random.

This idea is formalized by **H. P. Grice**

Grice's Cooperative Principle (Human Pragmatic Engine)

Four Maxims Humans Assume

Maxim	Human Expectation
Quantity	Say as much as needed
Quality	Say what is true
Relation	Be relevant
Manner	Be clear

Speech Acts: Language as Action

Based on
J. L. Austin

“Can you close the door?”

- Literal form: Question
- Intended act: **Request**

Humans automatically map:

- Form → function

Machines must **learn** this mapping.

Why Pragmatics Is Easy for Humans but Hard for Machines

- **Humans Have:**
  - Embodied experience
  - Social learning
  - Intent awareness
  - Cultural grounding
- **Machines Have:**
  - Text
  - Statistics
  - Patterns
  - No lived experience

Pragmatics is inference about minds — not words.

Early NLP and the Pragmatics Failure

Classical NLP assumed:

- Meaning is explicit
- Language is literal
- Rules are sufficient

Result:

- Chatbots that answered literally
- Failure with sarcasm, irony, hints

Example:

User: “Great, another bug.”
System: “Yes, bugs are insects.”

Total pragmatic failure

How Humans Learn Pragmatics ?

Humans learn pragmatics through:

- Interaction
- Feedback
- Social correction
- Consequences

Children learn:

- What *works*
- What *fails*
- What *offends*

Pragmatics is learned, not encoded.

How We Enable Machines to Handle Pragmatics ?

Large Language Models (Implicit Pragmatics)

LLMs learn pragmatics by:

- Exposure to massive conversational data
- Learning statistical regularities of intent
- Capturing indirect patterns

They can:

- Infer requests
- Handle implicatures
- Respond politely

But:

- No real intention
- No accountability
- Can hallucinate intent

Context Modeling

Modern systems track:

- Dialogue history
- Speaker roles
- Task goals

This approximates:

- Human conversational memory

Reinforcement Learning with Human Feedback (RLHF)

Humans reward:

- Helpful responses
- Polite tone
- Context-aware answers

Models learn:

- *“This kind of response is pragmatically appropriate.”*

This mirrors **social learning in humans**.

Explicit Pragmatic Challenges in NLP

Phenomenon	Why It’s Hard
Sarcasm	Literal meaning reversed
Irony	Requires shared knowledge
Politeness	Culture-dependent
Implicature	Meaning is implicit
Humor	Violates expectations

Current Limitations of Machine Pragmatics

Aspect	Humans	Machines
Intent	Internal	Inferred
Social norms	Learned experientially	Pattern-based
Repair	Self-aware	Error-prone
Accountability	Present	Absent

Thank You !