COP509

Natural Language Processing

From Fundamentals to 2025's Breakthroughs

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Learning Outcomes

By the end of this session, you will be able to:

1. Define Natural Language Processing and explain its core challenges
2. Describe how computers represent and process text (tokenisation, embeddings)
3. Identify key developments in Large Language Models (2017–2024)
4. Understand 2025's breakthrough: Large Reasoning Models
5. Evaluate the capabilities and limitations of current NLP systems

Outline

Part 1

What is Natural Language Processing?

Icebreaker: The AI Turing Test Game

Let's play a quick game!

Below are 2 short texts. Your task: Which one was written by AI, and which one by humans?

1. *"I needed something to help me with a language course. I suffer with mild deafness and this CD player and some earphones I have enable me to listen to the CDs and clearly hear their content. Plus whilst on Holiday and out walking I will be able to join all those other CD listeners. "*
2. *"I bought this CD player mainly to use with a language learning course, and it's been really helpful. The sound is clear when used with headphones, which makes a big difference for me, and it's comfortable to use for longer listening sessions. I also like how portable it is—I can take it out with me on walks or when I'm away from home. For the price, it does exactly what I needed it to do, and it arrived quickly as well."*

Discuss with your neighbour: Which is which? What clues did you use?

(Answer will be revealed after 2 minutes of discussion!)

Which was AI-generated?

- **Text 1:** Human (natural, evocative language, review from 1997 on a CD player)
- **Text 2:** AI (AI prompted to sound like human)

Key Insight: Distinguishing AI from human text is getting harder! Modern models are increasingly natural. By the end of today's lecture, you'll understand how they work.

Question: Did anyone guess these correctly? What gave away the AI text?

What is Natural Language Processing (NLP)?

Definition: Natural Language Processing is the branch of AI that enables computers to understand, interpret, and generate human language.

What NLP does:

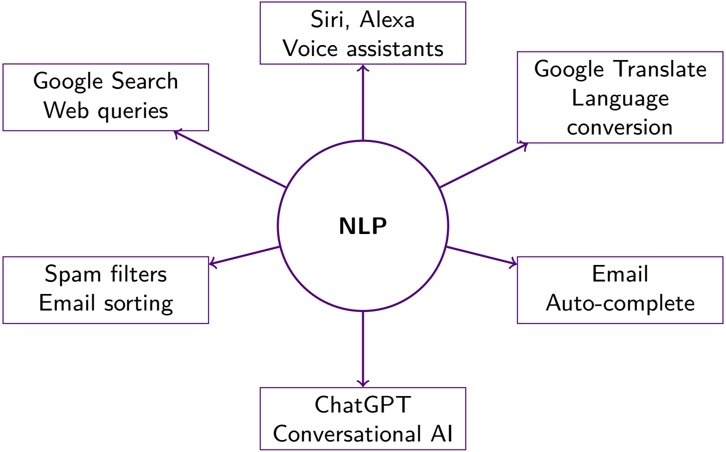
- Translates between languages
- Answers questions
- Summarises documents
- Generates human-like text
- Analyses sentiment
- Recognises speech

Why it's challenging:

- Ambiguity in meaning
- Context dependence
- Sarcasm and idioms
- Cultural nuances
- Grammar variations
- Multiple interpretations

Example of ambiguity: "I saw the man with the telescope"

- Did I use a telescope to see him? OR Was he holding a telescope?



You use NLP every day – often without realising it!
What AI tools do you use? and how often?

Part 2

Core NLP Concepts

How Do Computers Understand Text?

The Challenge: Computers only understand numbers (0s and 1s), not words!

The Solution: Convert Text → Numbers in two steps

Step 1 – Tokenisation: Break text into smaller units (tokens)

- Words: "Hello world" → ["Hello", "world"]
- Subwords: "unhappiness" → ["un", "happiness"]
- Why subwords? Handles new/rare words better

Real-world examples:

- **BERT** (WordPiece): "unhappiness" → ["un", "##happi", "##ness"]
- **GPT** (BPE): Uses ∼50,000 learned subword tokens

Step 2 – Embeddings: Convert each token to a numerical vector

- "cat" → [0.2, 0.8, 0.1, ... 300 numbers total]
- "dog" → [0.3, 0.7, 0.2, ... 300 numbers total]
- Similar meanings = Similar numbers!

Key Idea: Words with similar meanings are placed close together in mathematical space (like a map).

Language Models: Predicting the Next Word

What is a Language Model?
A statistical model that predicts the next word based on previous words.

Example: "The cat sat on the ___"

- Likely: "mat" (seen this phrase many times in training)
- Possible: "chair", "floor", "table"
- Unlikely: "sky", "ocean", "Tuesday"

How they learn: Trained on massive amounts of text (books, websites, articles) to learn patterns of language.

Traditional (2010s):

- Small models (millions)
- Limited context
- Task-specific

Modern (2020s):

- Large (billions)
- Long context
- General-purpose

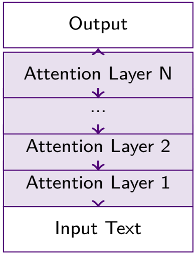
Part 3

The Transformer Revolution

The Transformer Architecture (2017)

Paper: "Attention is All You Need" by Vaswani et al., 2017
Why Transformers Changed Everything:

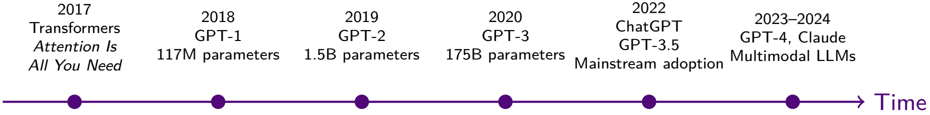
1. **Attention Mechanism:** Models learn which words are important. When the model processes the word "sat", it learns to pay attention to "cat" because that's the subject.
   - Example: In "The cat, which was black, sat" – "sat" pays attention to "cat"
2. **Parallel Processing:** Can process all words simultaneously
3. **Long-range Understanding:** Can connect words far apart in text



Each layer learns:
- Low-level: grammar
- Mid-level: syntax
- High-level: meaning

Impact: Foundation of all modern LLMs (GPT, BERT, Claude, etc.)

From GPT to ChatGPT: The LLM Journey



Key Trends: Language models became:

- **Larger** – scaled from 117M to 175B parameters, storing more linguistic patterns
- **More capable** – from sentence completion to essays, coding, and reasoning
- **More accessible** – ChatGPT reached around 100M users within months

Parameter: A learnable numerical weight. More parameters increase a model's capacity to learn complex patterns, at the cost of more data and computational resources.

Additional notes: GPT-3.5 / ChatGPT included instruction tuning and Reinforcement learning from human feedback (RLHF), improving helpfulness and safety.

Impact: These trends set the stage for multimodal and interactive LLMs such as GPT-4 and Claude.

Part 4

2025: The Year of Reasoning Models

2025's Game-Changer: Reasoning Models

The Big Shift: 2025 brought Large Reasoning Models (LRMs) that can "think" step-by-step before answering!

Traditional LLMs (2023–24):

- Quick responses
- Limited reasoning
- Sometimes confidently wrong
- Fixed output length

Reasoning Models (2025):

- Think before responding
- Show their reasoning process
- Self-correct mistakes
- Adapt time to difficulty

Simple analogy: Like a student showing their working on a maths exam rather than just writing the final answer. This lets teachers (or users) verify the logic.

Why this matters:

- More trustworthy (you can check the reasoning)
- Better at hard problems (can think longer)
- Easier to debug when wrong

Top 2025 Breakthrough: DeepSeek-R1

Paper: "DeepSeek-R1: Incentivizing Reasoning Capability in LLMs via Reinforcement Learning" (January 2025)
Citations: One of the most influential papers of 2025!

What makes it special:

1. Uses **Reinforcement Learning (RL)** to learn reasoning
   - Like training a dog: reward good behaviour, learn from mistakes
2. No human examples of reasoning needed – discovers strategies itself
3. Naturally develops advanced behaviours:
   - Breaking problems into manageable steps
   - Checking its own answers for errors
   - Trying multiple solution approaches
   - Self-reflection: "Wait, let me reconsider..."

Performance: Matches OpenAI's o1 model (proprietary) on mathematical reasoning
Open-source: Available in 6 sizes (1.5B, 7B, 8B, 14B, 32B, 70B parameters)
Models released: DeepSeek-R1-Zero and DeepSeek-R1

How Reasoning Models "Think"

Example: Solving a maths problem

Question: If a train travels 240 miles in 4 hours, what's its average speed?

Traditional Model Response:
"The answer is 60 mph."

Reasoning Model Response:
[Thinking] Let me work through this step by step:

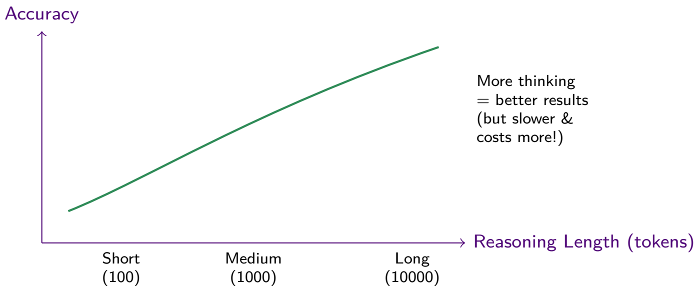
1. I need to find average speed $=$ distance $\div$ time
2. Distance $= 240$ miles
3. Time $= 4$ hours
4. Speed $= 240 \div 4 = 60$ mph
5. Let me verify: 60 mph $\times$ 4 hours $= 240$ miles ✓

[Answer] The average speed is 60 mph.

Key Benefit: You can see *how* the model solved it – makes it trustworthy and educational!

Chain-of-Thought: The Secret Sauce

What is Chain-of-Thought (CoT)?
A reasoning approach where models generate intermediate reasoning steps before the final answer.
Introduced by: Wei et al., 2022 ("Chain-of-Thought Prompting Elicits Reasoning in Large Language Models")
2025 Discovery: Longer reasoning chains = Better performance (but slower and more expensive!)



Trade-off: Longer CoT improves accuracy but increases computational cost and response time.

OptimalThinkingBench: Evaluating Over and Underthinking in LLMs

Other Major 2025 Innovations

1. **Multimodal Reasoning**
   - **Qwen2.5-VL**: Vision + language reasoning
   - **Vision-R1**: First multimodal reasoning with RL
   - Can reason about images, videos, and diagrams
2. **Test-Time Compute Scaling**
   - **s1: Simple test-time scaling**
   - Spend more compute time → get better answers
   - Like giving students more time for harder questions!
3. **Efficient Reasoning**
   - **CoT-Valve**: Dynamically adjusts reasoning length
   - **TokenSkip**: Skips unnecessary reasoning tokens
   - Reduces costs by 40% without sacrificing accuracy
4. **Small but Mighty Models**
   - **LIMO**: 1.5B model with 73.6% on MATH500
   - **s1-32B**: 7B models outperforming 70B models!
   - Key insight: High-quality data matters more than size

Part 5

Key 2025 Techniques

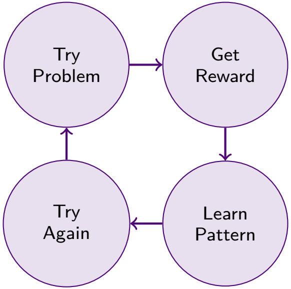
Reinforcement Learning for Reasoning

How do models learn to reason without human examples?

Reinforcement Learning: Learning through trial, error, and rewards

The Training Loop:

1. Model attempts problem
2. Gets reward for:
   - Correct answer
   - Valid reasoning steps
   - Proper format
3. Learns what works
4. Tries again, improves



Key Algorithms in 2025:

- **GRPO** (Group Relative Policy Optimization): Most popular
- **DAPO**: Open-source, achieves 50% on AIME 2024
- **PPO** (Proximal Policy Optimization): Traditional approach

Reward types: Correctness, format compliance, reasoning quality

The “Aha Moment” Phenomenon

Surprising 2025 Discovery: During RL training, models spontaneously develop advanced reasoning behaviours without being explicitly taught!

Paper: “Understanding R1-Zero-Like Training: A Critical Perspective”

Emergent Behaviours Observed:

- **Self-reflection:** “Wait, let me reconsider that...”
- **Verification:** Checking their own answers for correctness
- **Backtracking:** “That approach didn’t work, let me try another”
- **Self-correction:** Fixing mistakes mid-reasoning
- **Double-checking:** Verifying calculations independently

Analogy: Like a child learning to walk – they weren’t taught each individual muscle movement, but figured out the coordination through practice!

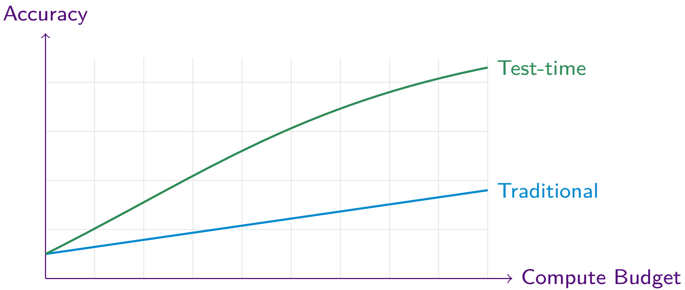
Research Question: Do models develop genuine problem-solving strategies, or just learn to mimic reasoning patterns? (Still debated!)

Key Finding: The “aha moment” occurs when verification behaviours suddenly emerge, typically after sufficient training on diverse problems.

Test-Time Compute: The New Scaling Law

Old Paradigm (2023–24): Bigger model = Better performance (fixed per question)
New Paradigm (2025): Same model + More thinking time = Better performance
Key Papers:

- "s1: Simple test-time scaling"
- "Can 1B LLM Surpass 405B LLM?")



Result: With test-time scaling, a 1B model can outperform a 405B model on some tasks! Same resources, much better results.
How it works: Allow model to generate multiple reasoning attempts, then select best one.

Part 6

Real-World Applications

2025 Models in Action

1. **Scientific Research**
   - **DeepSeek-Prover-V2**: Mathematical theorem proving
   - 88.9% success on MiniF2F-test benchmark
   - Solves 49 out of 658 PutnamBench problems
   - Solves 6 out of 15 AIME 2024–25 problems
2. **Software Development**
   - **SWE-RL**: Fixes real GitHub issues
   - 41% success rate on SWE-bench Verified
   - Debugging and writing production code
3. **Medical Diagnosis**
   - **Vision-R1**: Analyses medical images with step-by-step explanations
   - 73.5% accuracy on MathVista benchmark
   - Transparent reasoning helps clinicians verify decisions
4. **Education**
   - Step-by-step tutoring showing working
   - Adaptive to student understanding level
   - Can explain why an answer is wrong

Case Study: Mathematical Reasoning

Benchmark: AIME (American Invitational Mathematics Examination)

- Elite competition for top 2% of high school students
- 15 problems, 3 hours, requires advanced problem-solving

Model	Year	AIME 24	Notes
GPT-4	2023	1.8%	Early attempt
GPT-4o	2024	9.3%	Improved
DeepSeek-R1	2025	**79.8%**	RL-based
Qwen3	2025	**74.0%**	Unified framework
rStar-Math	2025	**53.3%**	MCTS-based
Top 20% students	–	*∼53%*	Human baseline

Remarkable Progress: In just 2 years, AI went from barely solving competition maths (1.8%) to exceeding most top human students (53%)!

Key insight: Test-time scaling allows models to "think longer" on hard problems, dramatically improving performance.

Beyond Text: Multimodal Reasoning

2025 Breakthrough: Models can now reason about images and videos!

Key Papers:

- **Qwen2.5-VL**: Vision-language understanding
- **Vision-R1**: First RL-based multimodal reasoning
- **VLM-R1**: Stable multimodal reasoning

Example: Solving geometry from images

1. [Sees] Image of triangle with two angles marked: 45° and 60°
2. [Thinks] "I can identify this is a triangle with two known angles"
3. [Recalls] "Triangle angle sum theorem: all angles $= 180°$"
4. [Calculates] "Third angle $= 180° - 45° - 60° = 75°$"
5. [Verifies] "$45 + 60 + 75 = 180$ ✓"
6. [Answer] "The unmarked angle is 75°"

Applications:

- Medical imaging with diagnostic explanations
- Autonomous vehicles reasoning about scenes
- Scientific diagram and chart interpretation

Part 7

Challenges and Future Directions

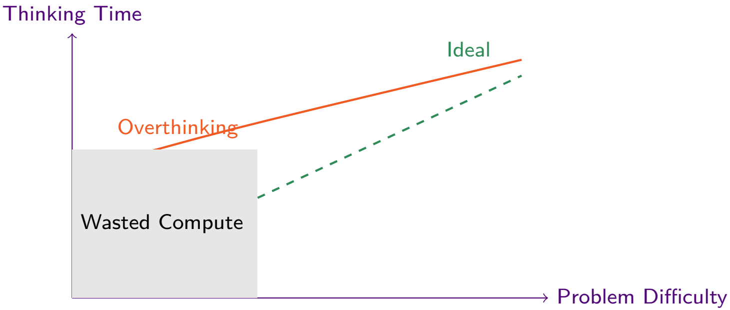
Current Limitations

Despite impressive progress, 2025 models still struggle with:

1. **Overthinking Problem**
   - Models sometimes spend too much compute on simple problems
   - Wastes time and money (computational resources)
   - **Solutions:** CoT-Valve, TokenSkip, Budget Forcing
2. **Hallucination**
   - Can generate confident but incorrect information
   - Reasoning helps reduce this, but doesn't eliminate it
   - Still an active research problem
3. **Computational Cost**
   - Long reasoning chains = expensive inference
   - Example: 10,000 token reasoning vs. 100 token answer (100x cost!)
   - Need efficiency improvements for practical deployment
4. **Faithfulness Question**
   - **Paper:** "Reasoning Models Don't Always Say What They Think"
   - Do models genuinely reason, or mimic reasoning patterns?
   - Important for trust and safety – ongoing debate

The Overthinking Phenomenon

Problem: Models don't know when to stop thinking – waste compute on easy problems!
Paper: "Stop Overthinking: A Survey on Efficient Reasoning"



2025 Solutions:

- **CoT-Valve**: Dynamically adjusts reasoning length based on confidence
- **TokenSkip**: Skips unnecessary intermediate steps
- **Budget Forcing**: Limits computation based on problem difficulty estimate

Goal: Match thinking time to problem difficulty – easy problems get quick answers, hard problems get more thought.

Open Research Questions

Theoretical Understanding:

- Why does RL spontaneously develop reasoning behaviours?
- What's the mathematical relationship between compute and capability?
- Can we prove guarantees about reasoning correctness?
- How to measure if reasoning is "genuine" vs. pattern matching?

Practical Challenges:

- How to make reasoning efficient enough for real-time applications?
- Can tiny models (1–3B parameters) match large model reasoning?
- How to verify reasoning is sound, not just plausible-sounding?
- Scaling to longer reasoning chains (100K+ tokens)?

Safety and Ethics:

- How to ensure models reason ethically?
- Can reasoning transparency improve safety and alignment?
- How to prevent models learning harmful reasoning patterns?
- Detecting and preventing "reward hacking" in training?

These are active research areas with many ongoing papers and projects!

Future Directions: 2026–27

Predicted developments based on current research trends:

1. **Continuous Learning Systems**
   - Models that improve from every user interaction in real-time
   - Learning from mistakes without full retraining
2. **Multi-Agent Reasoning**
   - Multiple AI models debating to reach better conclusions
   - Already emerging: constitutional AI, debate-based training
3. **Hybrid Neuro-Symbolic Systems**
   - Combining neural networks (learning) with formal logic (guarantees)
   - Provably correct reasoning for safety-critical applications
4. **Efficient Small Models**
   - 1–3B models with 70B-level reasoning capability
   - Deployable on phones, edge devices, wearables
5. **Long-Horizon Planning**
   - Models that plan complex multi-month projects
   - Autonomous scientific research and experimentation

Part 8

Summary

Exploring Reasoning Models

Want to see reasoning in action? Try these free platforms:

Commercial (Free Tiers):

- **ChatGPT o1** (OpenAI): Shows detailed reasoning for complex questions
- **Claude 4 Sonnet** (Anthropic): Extended thinking mode available
- **Gemini 2.5** (Google): Strong multimodal reasoning

Open-Source (Can Run Locally):

- **DeepSeek-R1**: Multiple sizes (1.5B to 70B)
- **Qwen3**: Supports 119 languages, thinking/non-thinking modes
- **s1-32B**: Efficient reasoning with small model

Experiment Ideas:

1. Ask a complex maths problem and observe the reasoning process
2. Compare reasoning mode vs. direct answer mode (speed vs. accuracy)
3. Give feedback on reasoning steps to see if model adapts
4. Test on problems from your own domain (programming, maths, etc.)

Prompt tip: Use "Think step-by-step and show your reasoning" for best results!

Key Takeaways

1. NLP enables computers to understand and generate human language
   - From search engines to conversational AI
2. Transformers (2017) revolutionised the field
   - Attention mechanism, parallel processing, long-range understanding
3. 2025 is the year of reasoning models
   - Models that "think" step-by-step before answering
   - Learnt through reinforcement learning, not supervised examples
   - Approaching and sometimes exceeding human expert-level
4. Key innovations: Chain-of-Thought, test-time compute scaling, multimodal reasoning, efficient small models
5. Challenges remain: overthinking, computational cost, hallucination, faithfulness
6. Exciting future: continuous learning, multi-agent systems, neuro-symbolic AI, efficient deployment

Bottom line: AI reasoning capabilities are advancing rapidly, with major implications for science, education, and society.

References and Further Reading

Essential Papers (All from 2025):

- DeepSeek-R1: Foundation of reasoning via RL
- Qwen2.5-VL: Multimodal reasoning
- Qwen3: Unified thinking/non-thinking framework
- "Towards Large Reasoning Models": Comprehensive survey
- "Stop Overthinking": Efficiency survey

Paper information sourced from **thebestnlppapers.com**

Code and Models:

- **Hugging Face**: Hub for pre-trained models
- **GitHub**: DeepSeek-R1, Qwen3, s1, rStar-Math repositories
- **APIs**: OpenAI, Anthropic, Google for latest models

Learning Resources:

- **Stanford CS224N**: NLP with Deep Learning (free online)
- **"Speech and Language Processing"** by Jurafsky & Martin (free textbook)
- **Anthropic's research blog**: Constitutional AI and safety

Questions?

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