Interpretability on How Large Language Models Process Information

From Tokens to Reasoning

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Overview

Level 1

General

“Before we explain *how* they work,
we must ask: *what* they are.”

Back to Index

What Is a Large Language Model?

- A model trained to predict the next word in a sequence.
- Learns from billions of words (web, books, conversations).
- Generates fluent language but doesn't "know" facts.
- Analogy: autocomplete on steroids.

`Input: The weather today is` ⇒ `sunny`

Where Are LLMs Used Today?

- Chatbots
- Email writing
- Code generation
- Tutoring
- Summarization
- Translation
- Poetry & fiction
- Research assistance
- Brainstorming
- Game narrative tools

LLMs aren't one tool — they're a toolbox.

ChatGPT: The Breakout Moment

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- Used for:
  - Homework help, coding, resumes
  - Legal briefs, medical advice (sometimes incorrectly)
  - Conversation, companionship, therapy prompts
- Sparked debates:
  - Is this cheating?
  - Should it be banned in classrooms?
  - Who's responsible for mistakes?

ChatGPT showed not just what LLMs can do — but how unprepared society was.

Prompt Design

- **Be clear and explicit.** Don't assume the model knows your intent.
- **Provide context.** Include relevant information (e.g., audience, tone).
- **Specify the output format.** List? Table? Email?
- **Use examples.** Show what you want with demonstrations.
- **Iterate.** Refine prompts to improve quality.

Less Effective Prompt:

- "Write me a thunderstorm poem."
- No format, no constraints, unclear tone.

More Effective Prompt:

- "Write a haiku (3 lines, 5-7-5) about a thunderstorm. Use vivid imagery."
- Clear task, form, and style guidance.

Better prompts → better results: LLMs follow instructions, not intentions.

What Is Hallucination?

- An LLM may generate confident but **false** statements.
- It's not lying — it just predicts what sounds plausible.
- The output isn't grounded in real knowledge.

```
"Hawaiian pizza was invented in Hawaii in 1962."
```

The correct origin of Hawaiian pizza is Ontario, Canada.
Fluency $\neq$ *truth.*

LLMs Are Not Search Engines

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- Google **retrieves** — it looks up from a database.
- LLMs **generate** — they synthesize based on probability.
- They don't verify facts or cross-check reality.
- Tools like RAG *try* to fix this, but not always reliably.

When you ask an LLM a question, you're getting a best guess — not a lookup.

Why Level 1 Matters

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Quote: "Every tool is safe — if you know what it can't do."

Roadmap

- ~~Level 1: General~~
- **Level 2: Novice**
- Level 3: Intermediate
- Level 4: Advanced
- Level 5: Expert

Level 2

Novice

"Understanding why LLMs behave the way they do — and why they sometimes fail."

▸ Back to Index

How Language Models Evolved

Symbolic AI (pre-2010)

- Rule-based systems
- Logic + search trees
- Expert systems
- High transparency

Neural AI (2010–2018)

- Feedforward networks
- RNNs / LSTMs / GRUs
- Word2Vec, GloVe embeddings
- Sequence learning, but limited memory

LLMs (2018–Now)

- Transformers: attention-based
- Self-supervised pretraining
- Contextual embeddings
- Emergent generalization

From rules → patterns → prediction at scale.

What Are Tokens?

- LLMs don't read raw words or sentences — they use **tokens**.
- A token is a chunk of text: word, subword, or character.
- Depends on the tokenizer (e.g., Byte Pair Encoding, SentencePiece).

Input:

- `"Understanding transformers is difficult."`

Tokenized:

- `["Understand", "ing", "transform", "ers", "is", "difficult", "."]`

Tokens are the model's language building blocks — not letters nor words.

What Are Embeddings?

- Tokens are converted into high-dimensional vectors called **embeddings**.
- Each embedding captures syntactic and semantic info.
- These vectors are learned during training.

$$\text{Token: ``dog''} \rightarrow \vec{v}_{\text{dog}} \in \mathbb{R}^d$$

Example: $d = 768$ or 1024 for small models.

Embeddings let neural networks process language numerically.

What Is Attention?

- Attention lets the model **weigh the importance** of each token in context.
- Instead of reading token in sequence, it looks at everything — and decides what to focus on.
- Each token attends to other words before making a prediction.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right) V$$

Q = query, K = key, V = value — all vectors derived from input embeddings.

Attention is how LLMs "decide what matters" for every token.

What's Going On Inside an LLM?

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$$x_1, \ldots, x_{t-1} \to \text{Embedding} \to \text{Transformer} \to P(x_t \mid x_{<t})$$

No memory. No long-term knowledge. Just context.

Why Do Hallucinations Happen?

- LLMs optimize for likelihood, not truth.
- They output tokens that **sound** likely, not ones that are **verified**.
- No connection to ground truth or external facts.

$$\text{LLM objective:} \quad \max_{\theta} \sum_{t=1}^{T} \log P_{\theta}(x_t \mid x_{<t})$$

Fluency $\neq$ *factuality. Confidence* $\neq$ *correctness.*

LLMs Are Probabilistic

- For a given input, there is no single "correct" output.
- The model samples from a probability distribution:

$$P(x_t \mid x_{<t}) = \mathrm{softmax}(f_\theta(x_{<t}))$$

- Sampling parameters:
  - Temperature T: controls randomness.
  - Top-k: restricts to k highest-probability tokens.
  - Top-p: cumulative probability threshold.

Same prompt $\Rightarrow$ different completions.

Shallow Understanding, Deep Fluency

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Shallow Understanding, Deep Fluency

- LLMs often mimic correct reasoning without understanding it.
- They rely on statistical regularities, not causal models.
- Signs of deep understanding:
  - Generalization to novel contexts
  - Robustness to paraphrase
  - Consistency over long sequences

High perplexity $\Rightarrow$ *confusion. Low perplexity* $\not\Rightarrow$ *understanding.*

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Level 3

Intermediate

"How do we interpret model behavior — when we can only see what it says?"

Back to Index

RAG: Expanding Output Context

- RAG augments the LLM's prompt with retrieved documents from an external source.
- This aims to improve grounding and reduce hallucinations by conditioning generation on real-world evidence.
- It operates entirely at the input/output level — no model parameters are changed.
- Paired with source/reference attribution, this offers some semblance of interpretability.

Query $\rightarrow$ **Retriever** $\rightarrow$ Documents $\rightarrow$ **LLM** $\rightarrow$ Completion

RAG offers a partial correction: it reduces hallucination without solving interpretability.

Interpretability vs Explainability

- **Interpretability:** human-accessible understanding of behavior.
- **Explainability:** tools or proxies for providing such insight.
- **Output-based analysis:** observes *what* the model does, not *how*.

At this layer, the output is our microscope.

Output-Based Layer

- **Generated text**: the final tokens predicted.
- **Log probabilities**: likelihoods assigned at each step.
- **Sampling behavior**: controlled by temperature, top-k, top-p.
- **Response variability**: rerun sensitivity to prompt tweaks.

$$P(x_t \mid x_{<t}) = \mathrm{softmax}(f_\theta(x_{<t}))$$

Output-based methods analyze what the model chooses to say.

Generated Text

- The most direct artifact of model behavior.
- Useful for analyzing fluency, coherence, style, and factual consistency.
- Provides first-pass insight into reasoning patterns, errors, and implicit biases.

Example Output (Same Prompt, Two Models)

`Prompt: "What caused the EDSA People Power Revolution?"`

Model A: "The revolution was a response to electoral fraud and declining public trust in the Marcos Sr. administration."

Model B: "The EDSA Revolution was sparked by U.S. interference and elite interests aiming to replace Marcos Sr."

Interpretation: Differences in factual emphasis, framing, and specificity reflect training biases and generalization behavior.

Log Probabilities

- Every token is assigned a log-probability.
- Can reveal:
  - Which words are "expected" or "surprising."
  - Where uncertainty spikes — hinting at confusion or ambiguity.

Example:

```
Prompt: "What was the popular name for the three Filipino priests executed by a garrote in 1872?"
Candidates: GomBurZa (0.91), MaJoHa (0.04), TitoVicJoey (0.01)
```

Low entropy = confidence; high entropy = uncertainty. Useful for detecting hallucination zones.

Sampling Behavior

- LLMs don't output a single deterministic result.
- Sampling parameters:
  - Temperature (T): randomness.
  - Top-k: limit to k most likely tokens.
  - Top-p: nucleus sampling.
- These affect coherence vs creativity trade-off.

Example:

`Prompt: "Write an opening sentence for a sci-fi novel."`

Top-k $=$ *1:* "The ship arrived."

Top-k $=$ *50:* "Starlight spilled across the ruins of Mars as Captain Oloyemi stepped out of cryo."

Sampling analysis helps probe model fluency vs surprise.

Prompt Sensitivity

- Small prompt changes can cause major output shifts.
- Useful for probing robustness and adversarial sensitivity.
- Sensitivity indicates shallow or unstable generalization.
- Interestingly, making prompts more rewarding, more respectful, or more terrifying, forces LLMs to behave differently.

Example:

```
Prompt A: "Summarize the article."
Prompt B: "Please summarize the article."
Prompt C: "Summarize the article in three points."
```

Analysis: How consistent is output across near-equivalent prompts?

Few-Shot Prompting

- More than a usage trick — it acts as a **behavioral probe**.
- Adds example Q&A pairs to the prompt to guide model behavior.
- Tests the model's ability to:
  - Recognize patterns in-context
  - Generalize from limited data
  - Simulate learning without weight updates

Example Prompt

```
Q: Translate "book" to French.
A: livre
Q: Translate "cat" to French.
A:
```

This lets us observe what models infer, not just what they memorize.

Chain-of-Thought (CoT)

- CoT encourages step-by-step output.
- Useful for arithmetic, logic, and reasoning probes.
- Exposes LLMs' ability to follow (or fake) structure.

Example

```
Q: If Sam has 3 Sonny Angels and buys 2 more, how many
angels in total?
A: Sam has 3 Sonny Angels.  He buys 2.  3 + 2 = 5.
Answer:  5
```

Reasoning may be correct, mimicked, or brittle — CoT makes it visible.

Where Do We Go From Here?

Examining the output is only scratching the surface. We could go deeper. Each level opens more of the model — and more responsibility.

Roadmap

- ~~Level 1: General~~
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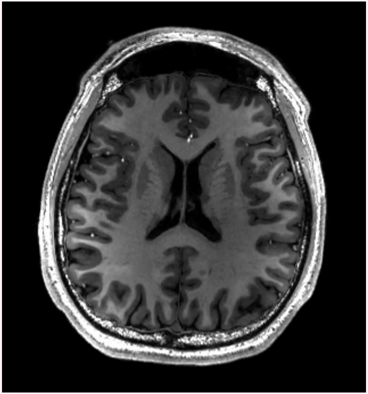
Level 4

Advanced

“Interpretability isn’t just about outputs — it’s about internal structure and function.”

Back to Index

Symptoms vs Causes



- Observing LLM outputs is like watching symptoms.
- You can spot patterns — but not mechanisms.
- To truly diagnose, we need an MRI: internal representations, layer activations, and causal circuits.

Surface clues help — but internal scans reveal the real picture.

Feature-Based Layer

- Goes beyond outputs to internal states — embeddings and activations.
- Methods:
  - Input attribution scores (e.g., Integrated Gradients)
  - Token-level importance (e.g., saliency maps)
  - Attention pattern heatmaps
  - Activation analysis: inspect hidden states layer by layer
- Enables hypothesis about what parts of the network respond to what inputs.

Feature-based interpretability opens the black box slightly

Attribution & Saliency

- **Input attribution scores**: quantify which input tokens influenced a decision.
- **Saliency maps**: gradient-based visualization of sensitivity per token.
- Typical techniques: Integrated Gradients, Gradient × Input, SmoothGrad.
- Useful for surfacing decision boundaries, detecting brittle reasoning.

Example (Sentiment Classification)

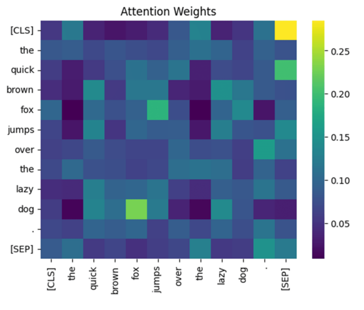
`Input: "I absolutely hated the movie."`

Salient Token: `"hated"` (high attribution score)

These methods expose which parts of the input drive model predictions — and whether they make sense.

Attention & Activations

- **Attention heatmaps**: visualize token-to-token attention weights.
  - Highlight long-range dependencies, alignment errors, or spurious focus.
  - Tools like **BertViz** support interactive exploration of attention patterns across heads and layers.
- **Activation analysis**: inspect internal states layer-by-layer.
  - Probe which neurons/layers fire for certain input types.
  - Can uncover specialization (e.g., syntax, entity tracking).



Example of attention heatmap

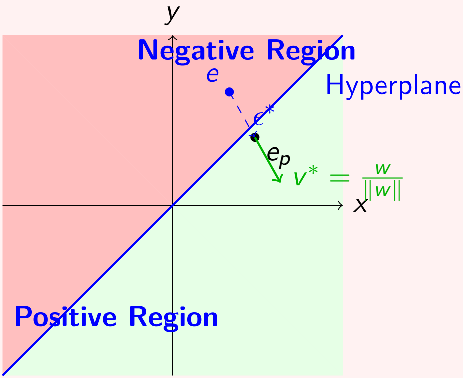
Concept Activation Vectors (CAVs)

- CAVs identify directions in activation space aligned with human-interpretable concepts.
- Originally from **TCAV** (Kim et al., 2018, vision); extended in NLP:
  - **SCAV** — toxicity axes (Xu et al., 2025)
  - **Bias-CAV** — identity framing, societal bias (Catapang, 2025)

CAVs cont'd.

Pipeline:

1. Collect labeled examples (e.g., biased vs. safe).
2. Train classifier on activations (usually linear).
3. Use the separating hyperplane as the concept direction v^*.



Mechanistic Layer

- Goes beyond analysis — aims for causal explanation of internal computation.
- Methods seek to reverse-engineer specific model behaviors:
  - Activation patching
  - Neuron/attention head tracing
  - Modular decomposition
- Goal: not just where or what — but **how** a model implements specific functions.

Mechanistic interpretability tries to open the engine — not just listening to how the engine hums.

Causal Tracing

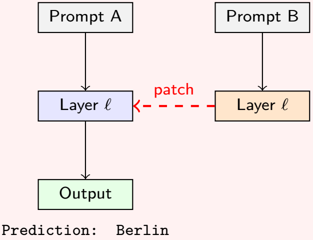
- Replace internal activations with those from other examples.
- If output changes $\Rightarrow$ the swapped layer mattered.
- **Technique:**
  1. Run two inputs (A and B)
  2. Patch activation from B into A at layer ℓ
  3. Observe effect on output
- Used to locate "where" specific behaviors are encoded.

Causal Tracing

Example Prompts:

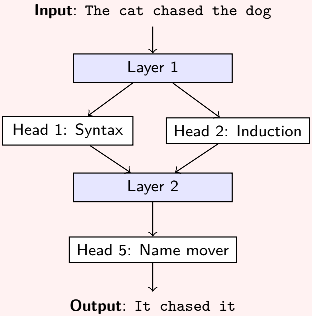
- A: “Paris is the capital of France.”
- B: “Berlin is the capital of Germany.”

→ *Patching B at layer ℓ changes output to “Berlin.”*



Modularity: Circuits, Heads, and Roles

- Transformers have specialized attention heads.
- **Induction head:** copies earlier token.
- **Name mover:** resolves coreference.
- **Syntax head:** tracks grammatical roles.
- Modular behaviors form circuits across layers.
- These circuits act like subroutines.



Goal

Map `input` → `head activity` → `output` to explain behavior causally.

Limitations & Open Challenges

- Scale: most circuit-level work is on small models (GPT-2, etc.)
- Polysemantic neurons: same unit fires for many unrelated concepts.
- Interdependence: behaviors often depend on distributed interactions.
- No guarantees: reverse-engineering is hard, brittle, and incomplete.

Mechanistic insight is promising — but remains aspirational at GPT-4 scale.

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Level 5

Expert

"Are we asking the right questions — or building deeper illusions?"

Back to Index

The Limits of Interpretability

- Not all model behavior is localizable or isolatable.
- Interpretability is often post hoc — narrative over mechanism.
- Most techniques are proxies: we don't know what we're missing.
- Can we ever "understand" a 175B parameter model?
- Do users want interpretability — or just reliability?

Interpretability gives the illusion of insight — but is that insight actionable?

Are LLMs the Right Architecture?

- Current LLMs are:
  - Autoregressive next-token predictors,
  - Largely inductive, not deductive,
  - Memoryless, goal-agnostic, and simulation-driven.
- Symbolic reasoning, long-term planning, abstraction are bolted on (e.g., RAG, agents, function calling).
- Core question: Can prediction truly yield reasoning?

We're training simulators — and asking them to become solvers.

The RAG Illusion

- RAG is often framed as a solution to hallucination — but it's a patch, not a cure.
- It still relies entirely on the LLM to interpret and generate from retrieved data.
- Retrieval does not constrain generation — it merely adds inputs.
- The core model remains:
  - Unverifiable,
  - Unfaithful to sources,
  - Unaware of retrieval provenance.
- The illusion: retrieval = truth $\Rightarrow$ generation = fact. **Not guaranteed.**

RAG is helpful — but it does not resolve the unreliability of the generator itself.

Skepticism: Are LLMs a Dead End?

- Critics argue LLMs:
  - Mimic reasoning, but don't possess it.
  - Encode bias and brittleness at scale.
  - Lack grounding, goals, or understanding.
- Alternative views:
  - Neuro-symbolic hybrids (LLMs + planning + logic).
  - Small, specialized models (MoE, retrieval agents).
  - Whole new paradigms (active inference, memory transformer, JEPA-like architectures (LeCun, 2022)).

LLMs are powerful — but perhaps wrong-shaped for general intelligence.

Philosophy: What Is Understanding?

- Is behavior sufficient for understanding?
- Can internal structure without intentionality be meaningful?
- How do we distinguish simulation vs comprehension?
- Is interpretability about *our* understanding — or the model's?

Quote: "If a model can explain itself — do we trust it more, or fear it more?"

Interpretability is not just a technical problem — it's a philosophical one.

The Future of LLM Research

- Toward models that:
  - Can reflect and reason over their own output,
  - Maintain consistent memory or self-state,
  - Integrate symbolic reasoning with deep priors.
- Interpretability will require:
  - Better tools (scalable probing, causal abstraction),
  - New norms (transparency standards, auditing),
  - A cultural shift from magic to mechanism.

Future models must not only generate — but justify.

Takeaways

- **Interpretability is layered.**
  - From outputs → features → mechanisms.
- **LLMs are powerful, but limited.**
  - Fluent, but not grounded.
  - Consistent, but not reflective.
- **Techniques exist — but insight is fragile.**
  - Attribution, patching, probing offer glimpses.
  - Causality remains elusive at scale.
- **The future may lie beyond LLMs.**
  - Toward modularity, memory, planning, and predictive representations.
  - Paradigms like JEPA reimagine what reasoning could mean.

Interpretability is not just a tool — it's a mirror. It reveals both the model and our assumptions about intelligence.

End

"By far, the greatest danger of artificial intelligence is that people conclude too early that they understand it."
— Eliezer Yudkowsky

Thank you for listening!

If you have questions, please email me at `jasperkylecatapang@gmail.com`.

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Backup Q&A Index

- Opinion: Do LLMs Really Understand What They Say?
- Opinion: Are LLMs a Dead End?
- How Is Attention Different from Memory?
- Why Do We Expect Deterministic Outcomes from Randomness?

Attention vs. Memory?

- **Attention** is *contextual weighting* — deciding what tokens to focus on now.
- **Memory** implies long-term storage and retrieval — across time or sessions.
- Transformers attend to all tokens in the current window — but forget everything after.
- *No state is saved* between prompts unless explicitly engineered (e.g., with memory modules).

Attention is selective focus. Memory is persistent storage. LLMs natively have one — not the other.

Back to Index

Randomness → Deterministic Outcomes

- LLMs are probabilistic by design — sampling is non-deterministic unless constrained.
- But humans **perceive language deterministically** — we expect consistency and intent.
- This mismatch creates confusion:
    - "Why did it answer differently?"
    - "Can I trust this answer?"
- Determinism can be forced (e.g., greedy decoding), but at the cost of creativity and robustness.

LLMs are not bugs — our expectations of determinism are.

Back to Index

Opinion: Are LLMs a Dead End?

- LLMs are powerful — but they're not the final form of intelligence modeling.
- They are **inductive engines**: great at pattern recognition, but weak at causal reasoning, planning, abstraction.
- They simulate thought — not generate it.
- Future systems will likely integrate:
  - Symbolic reasoning
  - Explicit memory and planning
  - Multimodal grounding and feedback
- LLMs aren't a dead end — but they are **a phase**. A stepping stone, not a destination.

We need systems that reason — not just simulate reasoning.

Back to Index

Opinion: Can LLMs Really Understand?

- This is an **open debate** in the AI community — with strong views on both sides.
- **Skeptical view (LeCun, Bender):**
  - LLMs simulate language without grounding or intent.
  - Fluency emerges from statistical patterns, not comprehension.
  - No world model, no goals — just token prediction.
- **Pro-understanding view (Hinton, Mitchell):**
  - Some argue understanding is *emergent*, not binary.
  - LLMs exhibit flexible reasoning, analogy, and abstraction in context.
  - If their behavior mirrors comprehension, should we deny it?

Perhaps LLMs don't "understand" like we do — but maybe they understand differently.

Back to Index