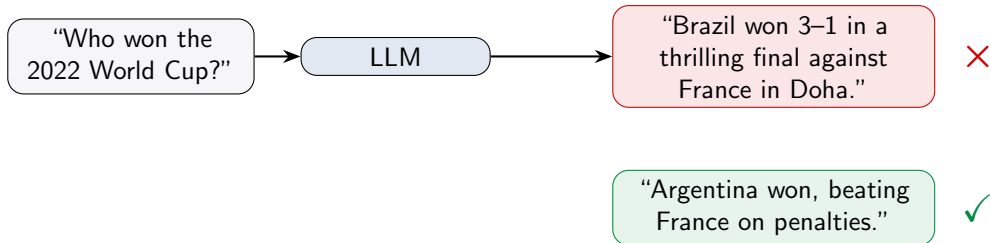


Hallucination & Grounding

Detection · Mitigation · Calibration · Attribution

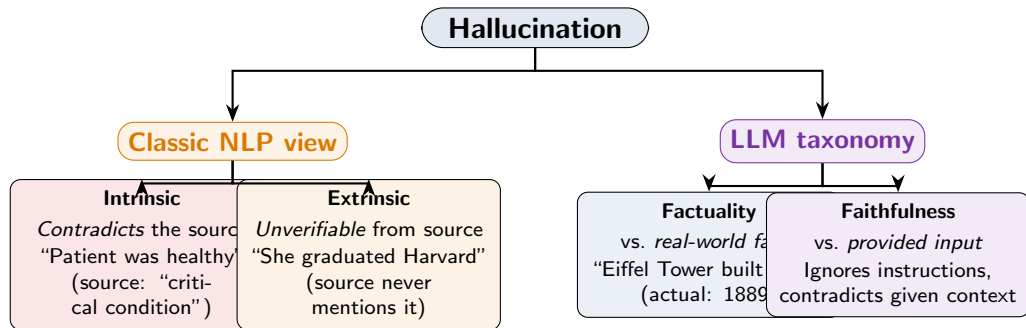
What is hallucination?



Hallucination: generated content that is **fluent, confident, and plausible** — but factually wrong or unsupported by any source.
Not random noise. Coherent, detailed fabrication.

The model doesn't "know" it's wrong — it produces the statistically most likely continuation.

Taxonomy of hallucinations



Maynez et al., ACL 2020

Huang et al., ACM TOIS 2024

Faithfulness sub-types: instruction inconsistency (wrong task) · context inconsistency (ignores RAG docs) · logical inconsistency (self-contradicts)

Types of hallucination

Factual errors

Confidently wrong facts
“The Great Wall is visible from space”

Fabricated citations

Non-existent references
GPT-3.5: 55%
of generated
citations are fake

Entity confusion

Merging attributes
of different entities
Wrong person's discoveries

Temporal confusion

Wrong dates, mixing eras
Post-cutoff confabulation
about recent events

Confabulation

Detailed fictional narratives
presented as fact
Entirely invented backstories

The danger: hallucinations are not random — they are *coherent*, *detailed*, and *confident*, making them hard to detect without external verification.

Walters & Wilder, *Scientific Reports*, 2023 · Ji et al., *ACM Computing Surveys*, 2023

Why LLMs hallucinate — training & architecture

Training data

Web-scale corpora contain contradictions, falsehoods, and outdated information.

The model learns *all* of it.

Exposure bias

Training: sees ground-truth prefix

Inference: sees its *own* outputs

Small early error \Rightarrow snowball

Objective mismatch

Trained to maximize
 $P(\text{next token} \mid \text{context})$
not $P(\text{correct token})$

Fluency \neq truthfulness

Softmax bottleneck

Hidden dim $d \ll \text{rank}(A)$
where A = true log-prob matrix

Yang et al., ICLR 2018

These are *structural* causes — they cannot be fully fixed by scaling alone.

Why LLMs hallucinate — generation dynamics

Temperature effects

$$P(x_i) = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$

High $T \rightarrow$ flat dist \rightarrow random

$T = 0 \rightarrow$ greedy traps

Sweet spot: $T \in [0.3, 0.7]$

Knowledge cutoff

Training data has a fixed temporal boundary.

Post-cutoff questions \Rightarrow plausible but fabricated answers

No world model

All “knowledge” is compressed into parameters — lossy.

No mechanism to distinguish *knowing* vs. *pattern-matching*

Knowledge conflicts

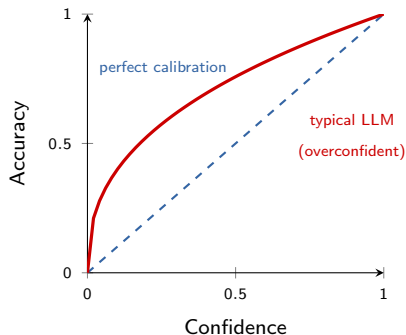
Parametric vs. contextual knowledge can disagree.

Popular entities: favor memory

Rare entities: favor context

Xie et al., EMNLP 2024

The confidence problem



$$\text{ECE} = \sum_{b=1}^B \frac{|B_b|}{N} |\text{acc}(B_b) - \text{conf}(B_b)|$$

Expected Calibration Error

RLHF makes it worse

Rewarding confident-sounding answers creates a confidence–accuracy gap

Verbalized confidence

“I’m 90% sure” is poorly calibrated — models default to high confidence regardless

Kadavath et al., 2022: “Language models (mostly) know what they know”

Real-world consequences

Legal

Mata v. Avianca (2023)

Lawyers used ChatGPT;
6 fabricated
case citations.

Judge fined them \$5,000.

Medical

Chatbots accepted false
medical claims **32%** of
the time.

Incorrect diagnoses risk
delayed treatment.

Academic

Fabricated citations enter
the literature.

“Hallucination
laundering”:

LLM fictions become
future training data.

Stanford study: LLMs hallucinate on legal queries **69–88%** of the time

GPT-3.5: 55% fabricated citations

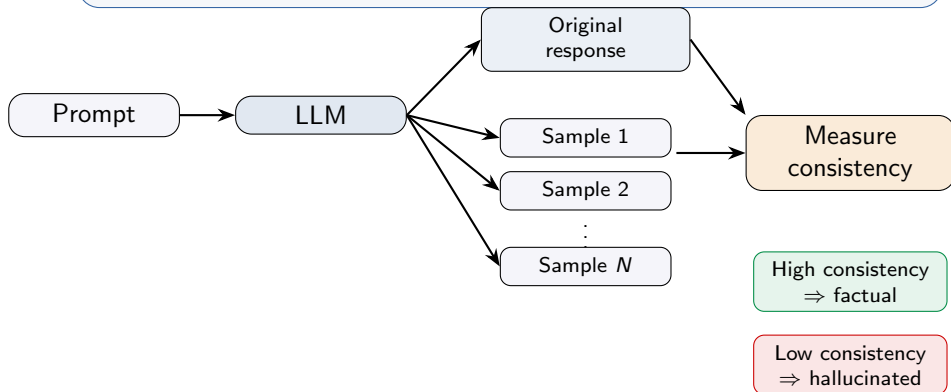
· **GPT-4:** 18% fabricated citations

Dahl et al., *Journal of Legal Analysis*, 2024

· Walters & Wilder, *Scientific Reports*, 2023

Detection: SelfCheckGPT

Key insight: if the model truly “knows” something, multiple stochastic samples will be **consistent**. Hallucinated facts will **vary** across samples.



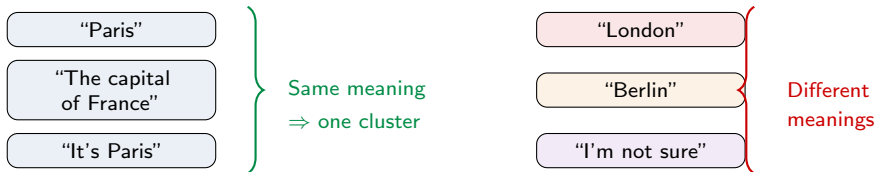
Zero-resource, black-box — no external databases, no model internals needed

Manakul et al., EMNLP 2023

Detection: Semantic Entropy

Problem: token-level entropy doesn't capture *meaning*.

"Paris" and "The capital of France" = different tokens, **same meaning**.



$$SE = -\sum_c P(c) \log P(c)$$

c = semantic clusters (not individual tokens)

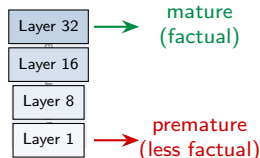
Low SE \Rightarrow consistent meaning
 \Rightarrow likely **correct**

Parquhar et al., Nature 2024

High SE \Rightarrow inconsistent meaning
 \Rightarrow likely **hallucinated**

Detection methods compared

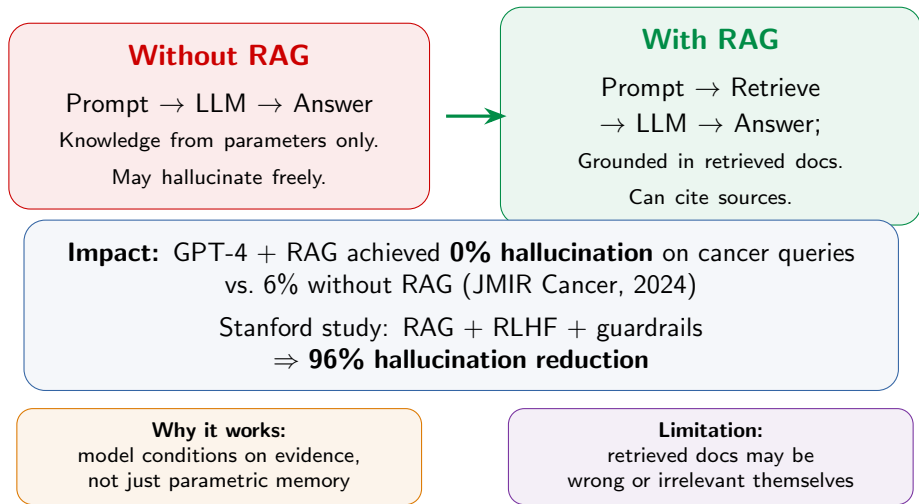
DoLa: Decoding by Contrasting Layers



Contrast late
vs. early logits
⇒ amplify factual signal
Chuang et al., ICLR 2024

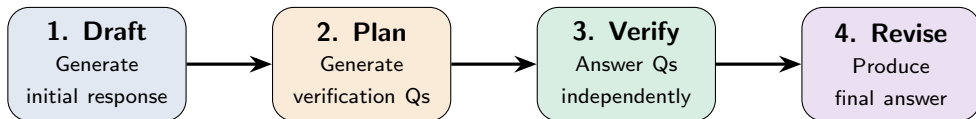
Method	Access	Key idea
SelfCheckGPT	Black-box	Multi-sample consistency
Semantic Entropy	Black-box	Meaning-level uncertainty
DoLa	White-box	Layer-contrastive decoding
Logit-based	White-box	Token probability thresholds
NLI-based	Black-box	Entailment checking vs. source

Mitigation: RAG as grounding



See our RAG lecture for full details · Lewis et al., NeurIPS 2020

Mitigation: Chain-of-Verification (CoVe)



Critical design: Step 3 is **decoupled** from the draft.
The LLM answers verification questions *without seeing its own draft*, preventing hallucinations from “poisoning” the verification step.

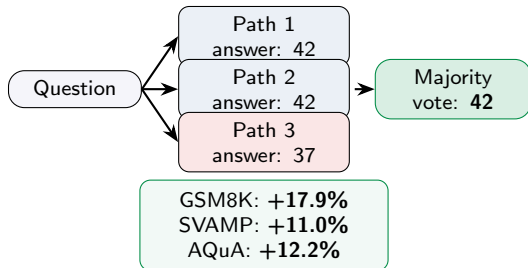
Result: 50–70% reduction in factual hallucinations on QA and long-form tasks

No extra training needed
Just a prompting strategy applied at inference time

Dhuliawala et al., ACL Findings 2024

Mitigation: Self-Consistency & constrained decoding

Self-Consistency (Wang et al., ICLR 2023)



Constrained Decoding

Contrastive decoding

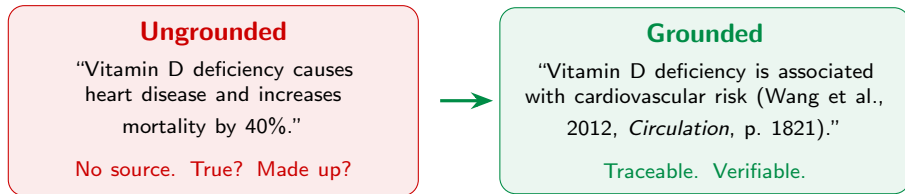
Contrast strong vs. weak model
(or late vs. early layers)
Amplify what the strong model
“knows” beyond the weak one

Key advantages:

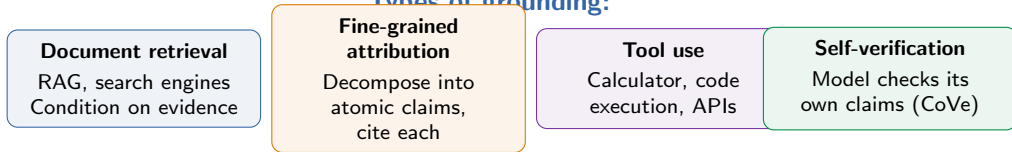
No extra training needed
Applied at inference time only
Complementary to RAG

Both approaches work at inference time — no retraining needed

Grounding & attribution



Types of grounding:

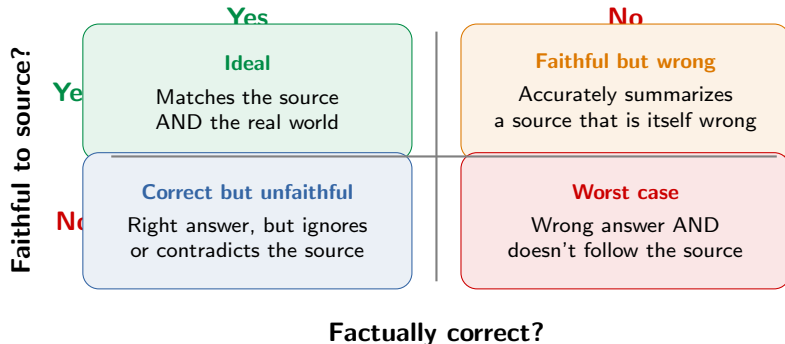


Principle: every claim should be traceable to a source.
If the model can't cite a source, it should say "I don't know."

Rashkin et al., ACL 2023 · Gao et al., NAACL 2024 · Schick et al., NeurIPS 2023

Faithfulness vs. factuality

Two independent dimensions of correctness

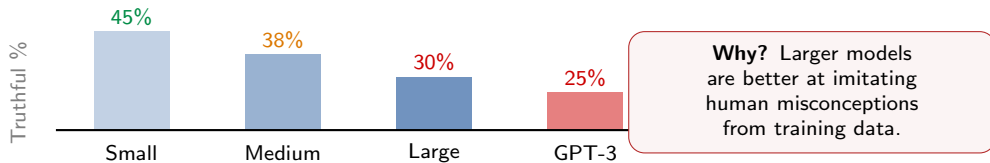


RAG settings: faithfulness matters more (follow the docs).
Open QA: factuality matters more (get the right answer).

Benchmarks for hallucination

Benchmark	Measures	Size	Key feature
TruthfulQA	Imitative falsehoods	817 Q	Inverse scaling
FActScore	Atomic factual precision	Per-gen	58% for ChatGPT (bios)
HaluEval	Hallucination detection	35K	QA, dialogue, summary
SimpleQA	Factual QA accuracy	–	Straightforward questions

TruthfulQA: inverse scaling — bigger models are less truthful



Lin, Hilton & Evans, ACL 2022 · Min et al., EMNLP 2023

The fundamental tension



Xu et al., 2024: formal impossibility proof

“Hallucination is inevitable for all computable LLMs”

All LLMs will hallucinate on *infinitely many* inputs, regardless of architecture, training algorithm, prompting technique, or training data.

The same mechanism
(exploring probability space)
produces both **creativity**
and **hallucination**

Practical implication:
don't try to eliminate
hallucination — instead,
detect and **manage** it

Saying “I don’t know”

Standard LLM

Always produces an answer,
even when uncertain.

“The answer is definitely X.”
(even when X is wrong)



Calibrated LLM

Refuses when uncertain,
expresses confidence levels.

“I’m not confident about this.
Let me search for sources.”

Epistemic uncertainty

Model doesn’t have enough
knowledge — **reducible**
with more data or retrieval

Aleatoric uncertainty

Inherent noise in the task
— **irreducible**
(ambiguous questions, etc.)

R-Tuning: refusal-aware instruction tuning · **US-Tuning:**
uncertainty-sensitive tuning (+34.7% on unknowns)

The mitigation landscape

When to apply each mitigation:

Training-time

RLHF for truthfulness
Factual fine-tuning
R-Tuning (refusal training)

Inference-time

RAG / tool use
CoVe, self-consistency
Constrained decoding (DoLa)

Post-hoc detection

SelfCheckGPT
Semantic entropy
NLI entailment checking

System-level

Human-in-the-loop review
Attribution requirements
Confidence thresholds

Defense in depth: no single method eliminates hallucination.
Best practice: **combine** training + inference + detection + system-level controls.

Stanford 2024: combining RAG + RLHF + guardrails achieved 96% reduction

Practical guide

What should I use?

Need factual answers?

⇒ **RAG + attribution**

Ground in retrieved docs,
cite every claim

Need reliable reasoning?

⇒ **CoT + self-consistency**

Multiple paths, majority vote

Building a product?

⇒ **Detect + flag uncertainty**

Semantic entropy, confidence
thresholds, human review

Research / evaluation?

⇒ **FActScore + SelfCheckGPT**

Measure hallucination rate,
track over model versions

Can't afford errors?

⇒ **Human-in-the-loop**

Legal, medical, financial

Want to reduce at training?

⇒ **RLHF + factual fine-tuning**

Expensive but most thorough

Further reading

Hallucination Surveys

- Ji et al. (2023), "Survey of Hallucination in Natural Language Generation"
- Huang et al. (2023), "A Survey on Hallucination in Large Language Models"
- Tonmoy et al. (2024), "A Comprehensive Survey of Hallucination Mitigation Techniques in LLMs"

Detection & Evaluation

- Manakul et al. (2023), "SelfCheckGPT: Zero-Resource Black-Box Hallucination Detection"
- Min et al. (2023), "FActScore: Fine-grained Atomic Evaluation of Factual Precision"

Mitigation Approaches

- Lewis et al. (2020), "Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks"
- Kadavath et al. (2022), "Language Models (Mostly) Know What They Know"

Questions?

Next: Mixture of Experts