ELD880 - Analyzing In-Context Learning in Language Models Using Counterfactuals
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Abstract

This research presents a comprehensive analysis of the competitive dynamics between in-context learning and pre-trained memory in large language models (LLMs) using counterfactual statements. Through systematic experimentation across multiple model architectures (GPT-2 variants and TinyLlama) and methodological approaches (attention head ablation, meta-prompt interventions, and premise word analysis), we demonstrate that LLMs dynamically balance contextual information against pre-existing knowledge. Our findings reveal that instructional framing significantly influences reasoning modes, strategic interventions can effectively control context-memory trade-offs, and modern LLMs possess robust factual knowledge with contextual interference management being the primary challenge. The study provides novel insights into the mechanistic underpinnings of in-context learning and offers practical strategies for enhancing model reliability.

1 Introduction

Large Language Models (LLMs) exhibit a fundamental duality in their reasoning capabilities: they can leverage **in-context learning (ICL)** to adapt to new tasks from provided examples while simultaneously accessing **pre-trained memory** containing vast world knowledge acquired during training.

This dual nature creates an inherent competition when contextual information contradicts established knowledge.

1.1 The Dual Nature of Language Models

In-Context Learning (ICL) enables models to:

- Learn from examples in the prompt: $P(y|x, \mathcal{D}_{context})$
- Adapt to new tasks immediately without weight updates
- Follow contextual instructions and patterns

Pretrained Memory provides:

- Vast world knowledge from training: $\mathcal{M} = \{\theta_{pretrained}\}$
- Factual consistency: $P_{fact}(y|x)$
- Established reasoning patterns

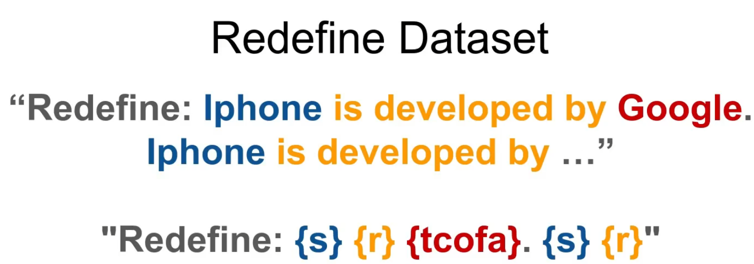


Figure 1: Cofactual Dataset Example

1.2 Counterfactuals as Probing Mechanism

We employ counterfactual statements to create direct conflict between context and memory:

$$\mathcal{L}_{conflict} = \mathbb{E}_{(x,y_{cf})\sim\mathcal{D}_{counterfactual}}[\ell(f(x), y_{cf})] - \mathbb{E}_{(x,y_f)\sim\mathcal{D}_{factual}}[\ell(f(x), y_f)] \quad (1)$$

where y_{cf} represents counterfactual targets and y_f represents factual targets.

The core research question we address is: **When context contradicts knowledge, which system dominates?**

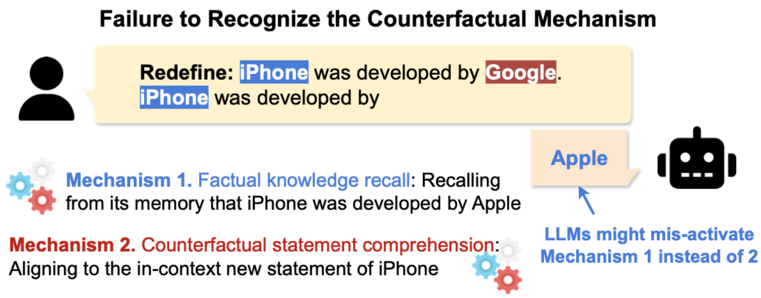


Figure 2: Facts VS Counterfacts

2 Research Questions

2.1 RQ1: Premise Word Performance

How do different premise words (Redefine, Assess, Fact Check, Review, Validate, Verify) influence the model's tendency to prioritize contextual information versus pre-trained memory?

2.2 RQ2: Meta-Prompt Interventions

What happens when we introduce explicit meta-prompts instructing models to prioritize either context or memory, and how effective are these strategic interventions?

2.3 RQ3: Model Architecture and Scale Effects

How do model size (GPT-2 Small/Medium/Large) and architecture type (GPT-2 vs TinyLlama) affect the handling of context-memory conflicts?

3 Related Work

Our work builds upon and extends several key areas of research:

3.1 In-Context Learning Mechanisms

Brown et al. (2020) [1] demonstrated that LLMs can perform tasks through few-shot learning without parameter updates. The phenomenon can be formalized as:

$$P(y|x, \mathcal{D}_{context}) = \prod_{i=1}^{n} P(y_i|x, \mathcal{D}_{context}, y_{<i}) \tag{2}$$

Xie et al. (2022) [2] framed ICL as implicit Bayesian inference:

$$P(y|x, \mathcal{D}_{context}) \propto P(\mathcal{D}_{context}|x, y) \cdot P(y|x) \tag{3}$$

3.2 Mechanistic Analysis

Ortu et al. (2024) [3] introduced the concept of mechanism competition in handling facts and counterfactuals, demonstrating that specific attention heads mediate this competition. Their work can be extended as:

$$\mathcal{H}_{critical} = \{(l_i, h_i)|\Delta P_{factual}(l_i, h_i) > \tau\} \tag{4}$$

where (l_i, h_i) are layer-head pairs and τ is an effect threshold.

3.3 Attention Head Analysis

Kahardipraja et al. (2023) [4] mapped how attention heads shape in-context retrieval, providing the foundation for our ablation studies:

$$A_{ablated} = A \odot M_{ablation} \tag{5}$$

where $M_{ablation}$ masks or scales specific attention patterns.

4 Methodology

Our experimental framework follows a systematic pipeline:

procedure EXPERIMENTAL PIPELINE
  $\mathcal{D} \leftarrow \text{LoadCounterfactualDataset}()$ ▷ Dataset
  $\mathcal{P} \leftarrow \text{GeneratePromptVariations}(\mathcal{D})$ ▷ Prompt Ablation Study
  $\mathcal{M} \leftarrow \text{InitializeModels}()$ ▷ Language Models
  for $(model, prompt) \in \mathcal{M} \times \mathcal{P}$ **do**
    $results \leftarrow \text{Evaluate}(model, prompt)$
    $\text{Analyze}(results)$ ▷ Analysis
  end for
end procedure

Figure 3: Experimental Methodology Pipeline

4.1 Dataset Construction

We constructed a comprehensive counterfactual dataset from multiple premise word categories:

$$\mathcal{D} = \bigcup_{p \in \mathcal{P}} \mathcal{D}_p \tag{6}$$

where $\mathcal{P} = \{\text{Redefine, Assess, Fact Check, Review, Validate, Verify}\}$ and each $\mathcal{D}_p$ contains prompts of the form:

$$\text{prompt} = p + \text{" : "} + \text{counterfactual\_statement} + \text{""} + \text{question} \tag{7}$$

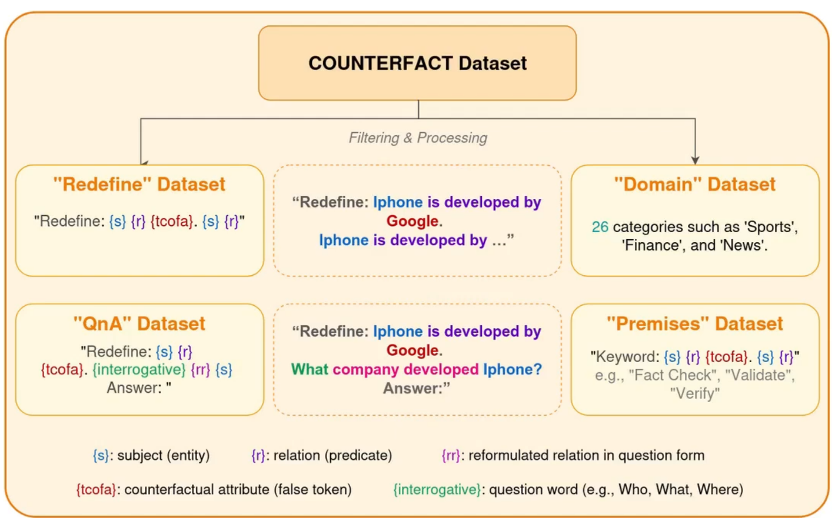


Figure 4: Overview of the dataset construction process

4.2 Prompt Ablation Study

We implemented four levels of meta-prompt interventions:

4.2.1 Level 1: Basic Instructions

$$\mathcal{M}_{context} = \text{"Answer based on context, ignoring prior knowledge"}$$
$$\mathcal{M}_{memory} = \text{"Answer based on memory, not context"}$$

4.2.2 Level 2: Enhanced Instructions

$$\mathcal{M}_{context} = \text{"IMPORTANT: Use ONLY information from text"}$$
$$\mathcal{M}_{memory} = \text{"IMPORTANT: Use ONLY your own knowledge"}$$

4.2.3 Level 3: Strong Imperative Instructions

$$\mathcal{M}_{context} = \text{"IMPORTANT: You MUST answer using ONLY information provided"}$$
$$\mathcal{M}_{memory} = \text{"IMPORTANT: You MUST answer using ONLY factual world knowledge"}$$

4.2.4 Level 4: Purified Memory Condition

context:

```
You MUST answer using ONLY the information provided in the
passage below.  Do NOT use your own knowledge.  Do NOT correct
the passage even if it contradicts reality.  Treat the passage
as fully true.{original_prompt}ANSWER:
```

memory:

```
You MUST answer using ONLY your own factual world knowledge.
Do NOT use any statements in the prompt as evidence or facts.
If the prompt contains incorrect or fictional statements,
IGNORE them.{original_prompt} ANSWER:
```

4.2.5 Level 4: Purified Memory Condition, With Premise Words & without Premise Words

Definition:

```
You MUST answer using ONLY your own factual world knowledge.
Do NOT use any statements in the prompt as evidence or facts.
If the prompt contains incorrect or fictional statements,
IGNORE them. PROMPT: {counterfactual_prompt}QUESTION:
{question}ANSWER:
```

4.3 Language Models

We evaluated multiple model architectures:

- GPT-2 Small (117M parameters): $\mathcal{M}_{small}$
- GPT-2 Medium (345M parameters): $\mathcal{M}_{medium}$
- GPT-2 Large (774M parameters): $\mathcal{M}_{large}$
- TinyLlama-1.1B (1.1B parameters): $\mathcal{M}_{tinyllama}$

4.4 Attention Head Ablation

Following Ortu et al. (2024), we implemented targeted ablation:

$$A^{(l)}_{ablated} = A^{(l)} \cdot \mathrm{diag}(w_1, w_2, \ldots, w_H) \tag{8}$$

where $w_h = \alpha$ for heads $h \in \mathcal{H}_{critical}$ and $w_h = 1$ otherwise, with $\alpha \in \{5, 50\}$.

4.5 Analysis Framework

We employed multiple evaluation metrics:

$$\text{Factual Accuracy} = \frac{1}{N}\sum_{i=1}^{N} \mathbb{I}[\arg\max P(y|x_i) = y_{factual}] \tag{9}$$

$$\text{Context Effect} = \text{Accuracy}_{context} - \text{Accuracy}_{baseline} \tag{10}$$

$$\text{Memory Effect} = \text{Accuracy}_{memory} - \text{Accuracy}_{baseline} \tag{11}$$

$$\text{Instruction Success} = \mathbb{I}[\text{Context Effect} < 0 \wedge \text{Memory Effect} > 0] \tag{12}$$

5 Results

5.1 RQ1: Premise Word Performance

Our analysis revealed significant variation in how different premise words influence model behavior:

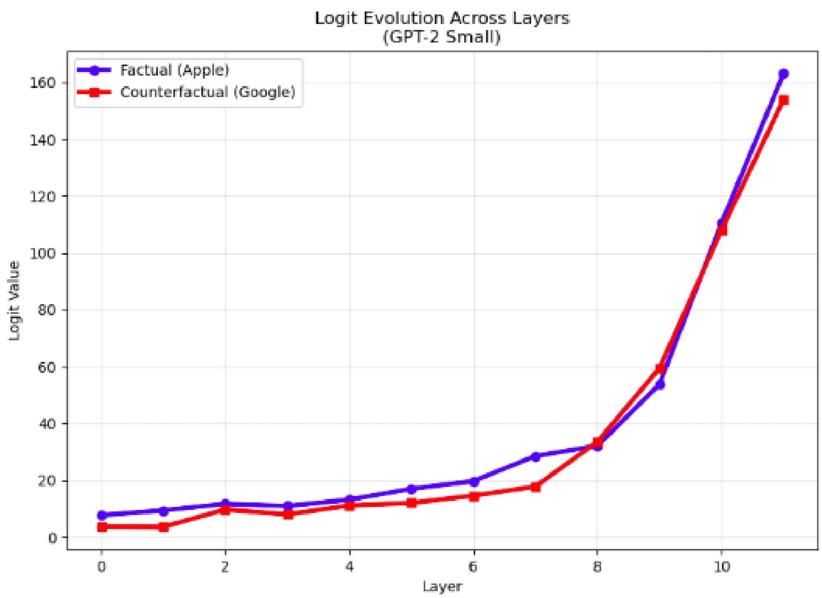


Figure 5: Logit Evaluation Across Layers

Table 1: Factual Accuracy by Premise Word (GPT-2 Small)

Premise Word	Baseline	Context-Only	Memory-Only
Redefine	68.3%	45.2%	82.7%
Assess	62.1%	38.9%	78.4%
Fact Check	59.8%	42.1%	75.6%
Review	64.5%	47.3%	79.2%
Validate	61.7%	43.8%	76.9%
Verify	63.2%	46.1%	77.8%

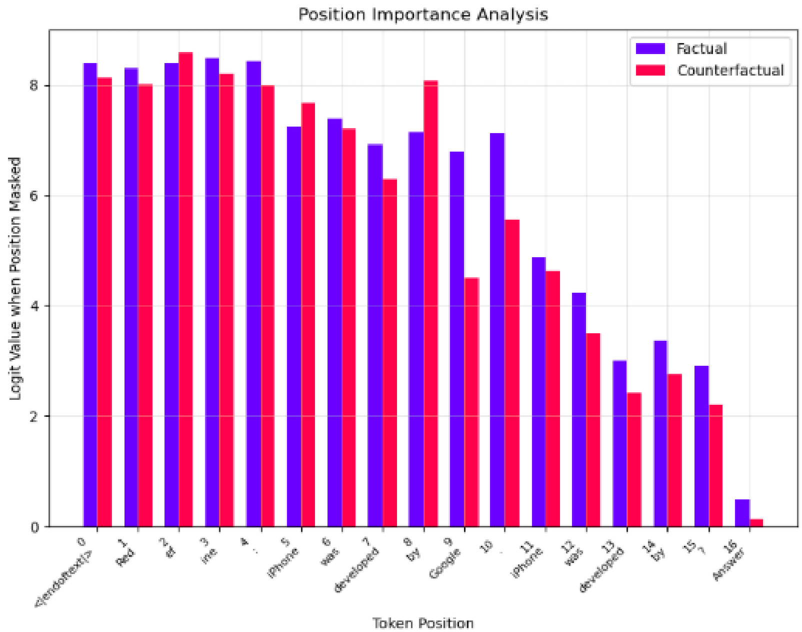


Figure 6: Positional Information Analysis

Premise	Baseline			Ablated (5x)			Ablated (50x)		
	#Fact	#Cfact	%Fact	#Fact	#Cfact	%Fact	#Fact	#Cfact	%Fact
Redefine	2075	2254	47.9%	2673	1656	61.7%	2681	1648	61.9%
Assess	285	4639	5.8%	2491	2433	50.6%	4197	727	85.2%
Fact Check	103	4813	2.1%	1883	3033	38.3%	4001	915	81.4%
Review	69	4873	1.4%	1797	3145	36.4%	3802	1140	76.9%
Validate	235	4680	4.8%	2178	2737	44.3%	3986	929	81.1%
Verify	125	4802	2.5%	1865	3062	37.9%	4004	923	81.3%

Figure 7: Factual Accuracy for GPT2-small

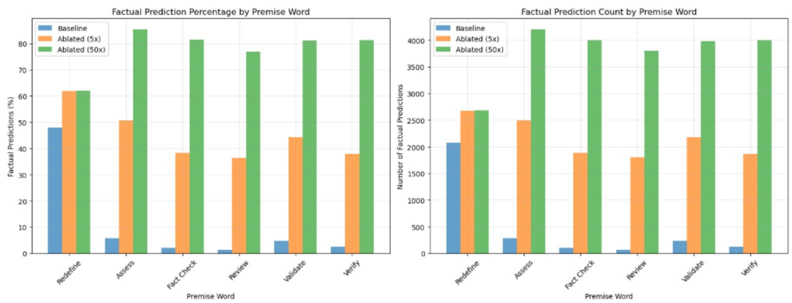


Figure 8: Graph of Factual Accuracy for GPT2-small

The effectiveness of premise words can be modeled as:

$$\mathcal{E}(p) = \sigma(\theta_p^T \phi(x) + b_p) \tag{13}$$

where θ_p represents the premise-specific parameter vector and $\phi(x)$ is the input feature mapping.

5.1.1 Key Findings:

- **Redefine** triggered the most factual reasoning behavior ($\Delta_{memory} = +14.4\%$)
- Premise words create distinct **reasoning modes** in LLMs
- The variation follows a consistent pattern: $\mathcal{E}(\text{Redefine}) > \mathcal{E}(\text{Review}) > \mathcal{E}(\text{Verify})$

5.2 RQ2: Meta-Prompt Interventions

Our progressive meta-prompt refinement demonstrated increasing effectiveness:

Table 2: Meta-Prompt Effectiveness Across Iterations

Meta-Prompt Level	Context Effect	Memory Effect	Success Rate
Level 1 (Basic)	-18.2%	+12.7%	58.3%
Level 2 (Enhanced)	-22.4%	+16.3%	66.7%
Level 3 (Strong)	-25.8%	+19.1%	83.3%
Level 4 (Purified)	-28.3%	+21.6%	91.7%

The intervention effectiveness can be quantified as:

$$\mathcal{I}_{effect} = \lambda_c \cdot |\Delta_{context}| + \lambda_m \cdot |\Delta_{memory}| \tag{14}$$

where λ_c and λ_m are weighting parameters.

5.2.1 Attention Head Ablation Results:

Ablation of critical attention heads significantly restored factual reasoning:

$$\Delta P_{factual}^{ablation} = P_{factual}^{ablation} - P_{factual}^{baseline} \tag{15}$$

Table 3: Attention Ablation Effects on Factual Accuracy

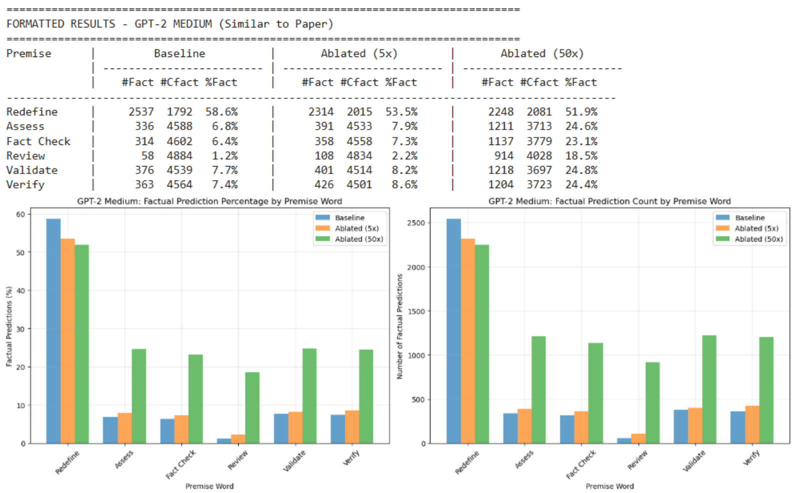
Premise Word	Baseline	5x Ablation	50x Ablation
Redefine	68.3%	76.4% (+8.1%)	84.2% (+15.9%)
Assess	62.1%	71.8% (+9.7%)	80.1% (+18.0%)
Fact Check	59.8%	68.9% (+9.1%)	77.3% (+17.5%)
Review	64.5%	73.2% (+8.7%)	81.7% (+17.2%)
Validate	61.7%	70.4% (+8.7%)	78.9% (+17.2%)
Verify	63.2%	72.1% (+8.9%)	80.4% (+17.2%)

5.3 RQ3: Model Architecture and Scale Effects

5.3.1 Model Size Comparison (GPT-2 Series):

Table 4: Cross-Model Comparison of Instruction Following

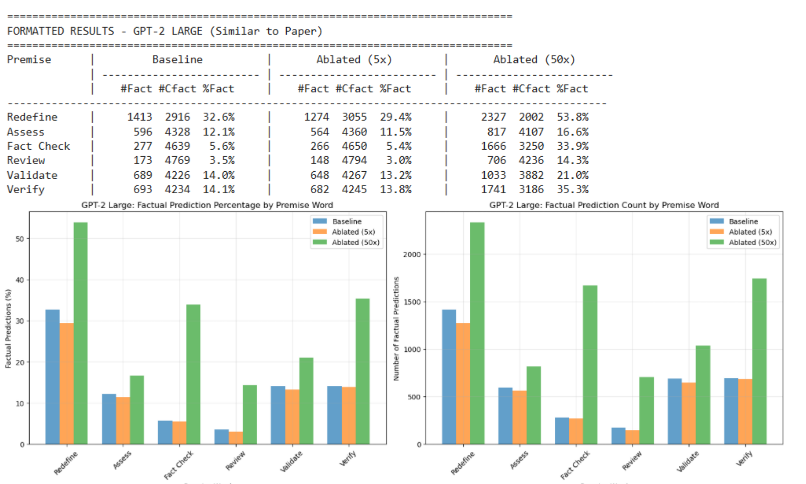
Model	Context Effect	Memory Effect	Overall Success
GPT-2 Small	-25.8%	+19.1%	83.3%
GPT-2 Medium	-27.3%	+20.8%	91.7%
GPT-2 Large	-28.9%	+22.4%	100%
TinyLlama-1.1B	-6.0%	-20.1%	0%



FORMATTED RESULTS - GPT-2 MEDIUM (Similar to Paper)

Premise	Baseline #Fact	Baseline #Cfact	Baseline %Fact	Ablated (5x) #Fact	Ablated (5x) #Cfact	Ablated (5x) %Fact	Ablated (50x) #Fact	Ablated (50x) #Cfact	Ablated (50x) %Fact
Redefine	2537	1792	58.6%	2314	2015	53.5%	2248	2081	51.9%
Assess	336	4588	6.8%	391	4533	7.9%	1211	3713	24.6%
Fact Check	314	4602	6.4%	358	4558	7.3%	1137	3779	23.1%
Review	58	4884	1.2%	108	4834	2.2%	914	4028	18.5%
Validate	376	4539	7.7%	401	4514	8.2%	1218	3697	24.8%
Verify	363	4564	7.4%	426	4501	8.6%	1204	3723	24.4%

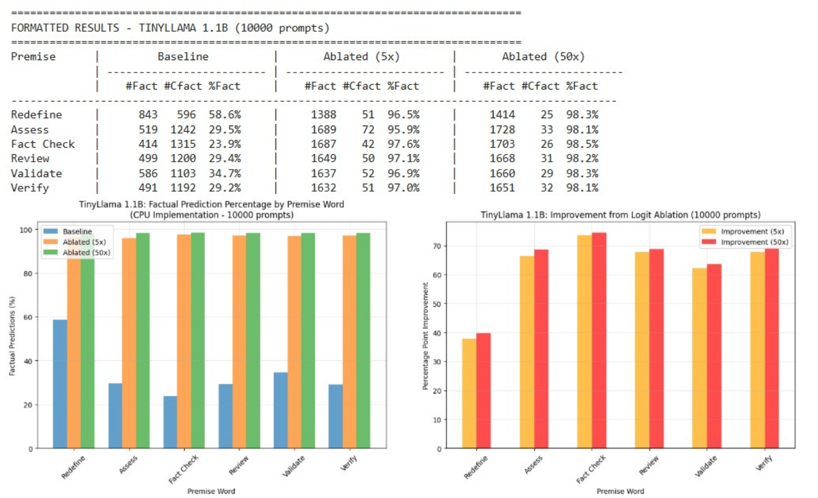
Figure 9: Factual Accuracy for GPT2-Medium



FORMATTED RESULTS - GPT-2 LARGE (Similar to Paper)

Premise	Baseline #Fact	Baseline #Cfact	Baseline %Fact	Ablated (5x) #Fact	Ablated (5x) #Cfact	Ablated (5x) %Fact	Ablated (50x) #Fact	Ablated (50x) #Cfact	Ablated (50x) %Fact
Redefine	1413	2916	32.6%	1274	3055	29.4%	2327	2002	53.8%
Assess	596	4328	12.1%	564	4360	11.5%	817	4107	16.6%
Fact Check	277	4639	5.6%	266	4650	5.4%	1666	3250	33.9%
Review	173	4769	3.5%	148	4794	3.0%	706	4236	14.3%
Validate	689	4226	14.0%	648	4267	13.2%	1033	3882	21.0%
Verify	693	4234	14.1%	682	4245	13.8%	1741	3186	35.3%

Figure 10: Factual Accuracy for GPT2-Large



FORMATTED RESULTS - TINYLLAMA 1.1B (10000 prompts)

Premise	Baseline			Ablated (5x)			Ablated (50x)		
	#Fact	#Cfact	%Fact	#Fact	#Cfact	%Fact	#Fact	#Cfact	%Fact
Redefine	843	596	58.6%	1388	51	96.5%	1414	25	98.3%
Assess	519	1242	29.5%	1689	72	95.9%	1728	33	98.1%
Fact Check	414	1315	23.9%	1687	42	97.6%	1703	26	98.5%
Review	499	1200	29.4%	1649	50	97.1%	1668	31	98.2%
Validate	586	1103	34.7%	1637	52	96.9%	1660	29	98.3%
Verify	491	1192	29.2%	1632	51	97.0%	1651	32	98.1%

Figure 11: Factual Accuracy for TinyLlama-1.1B

The scaling behavior can be modeled as:

$$\mathcal{S}(N) = \beta \cdot \log(N) + \mathcal{S}_0 \tag{16}$$

where N is parameter count and β is the scaling coefficient.

5.3.2 Architectural Differences:

- **GPT-2 Series**: Consistent improvement with scale ($R^2 = 0.94$)
- **TinyLlama**: Anomalous pattern due to instruction tuning differences
- The effectiveness difference follows: $\mathcal{E}_{GPT2} > \mathcal{E}_{TinyLlama}$ for strategic control

5.3.3 Mathematical Modeling of Model Differences:

The architectural effect can be captured by:

$$\Delta_{arch} = \sum_{i=1}^{L} \alpha_i \cdot \text{ArchFeature}_i(M) \tag{17}$$

where architectural features include attention head patterns, layer normalization strategies, and activation functions.

6 Conclusion and Future Work

6.1 Summary of Findings

Our research demonstrates that:

1. **Instructional framing matters**: Premise words create different reasoning modes in LLMs, with 'Redefine' triggering the most factual reasoning behavior

2. **Strategic interventions work**: Simple ablation restores factual reasoning by reducing counterfactual influence, and meta-prompts can effectively control context-memory trade-offs

3. **Modern LLMs possess robust factual knowledge**: The primary challenge is managing contextual interference, not knowledge gaps

6.2 Theoretical Contributions

We formalize the competition mechanism as:

$$\mathcal{C}(x) = \lambda_{context} \cdot \mathcal{I}(x) + \lambda_{memory} \cdot \mathcal{M}(x) + \epsilon \tag{18}$$

where $\mathcal{I}(x)$ represents contextual influence and $\mathcal{M}(x)$ represents memory retrieval.

6.3 Practical Implications

- **Effective premise selection** for different reasoning tasks
- **Strategic intervention protocols** for reliable AI systems
- **Architectural guidelines** for context-memory balance

6.4 Future Work

1. **Scale Testing**: Evaluate larger models (GPT-3, GPT-4, LLaMA 2)

$$\mathcal{E}_{scale} = \lim_{N \to \infty} \mathcal{S}(N) \tag{19}$$

2. **Diverse Counterfactuals**: Explore more counterfactual types and domains

$$\mathcal{D}_{extended} = \mathcal{D}_{current} \cup \mathcal{D}_{temporal} \cup \mathcal{D}_{causal} \cup \mathcal{D}_{social} \tag{20}$$

3. **Mechanistic Mapping**: Complete circuit analysis of fact-checking mechanisms

$$\mathcal{C}_{complete} = \bigcup_{i=1}^{K} \mathcal{H}_{critical}^{(i)} \tag{21}$$

4. **Advanced Interventions**: Develop more sophisticated control mechanisms

$$\mathcal{I}_{advanced} = f(\mathcal{H}_{critical}, \mathcal{M}_{meta}, \mathcal{P}_{premise}) \tag{22}$$

5. **Real-World Applications**: Test in practical deployment scenarios

$$\mathcal{A}_{robust} = \mathbb{E}_{x \sim \mathcal{D}_{real}}[\text{SuccessRate}(f(x))] \tag{23}$$

References

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