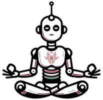
# Inverse Language Modeling towards Robust and Grounded LLMs

## Master's Degree in Computer Science

**Simone Sestito** (1937764)

Academic Year 2024/2025



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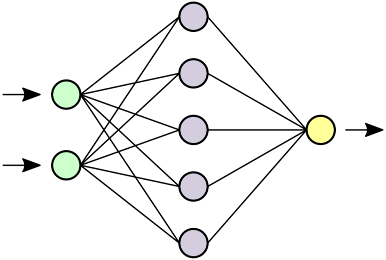
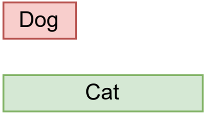
We want to **change the input** to minimize the loss

Input image



Neural Network




Output Distribution

# Adversarial Input



The optimized perturbation $\delta$ may look like:

Input image

$+\,\alpha\cdot$

Noise

$\Rightarrow$

**Adversarial image**

# Adversarial Training



A classifier can be made robust using **Adversarial Training**:

- Generate $\mathbf{x}'$ samples
- Include them in the training process
- Repeat

# Adversarial Training

A classifier can be made robust using **Adversarial Training**:

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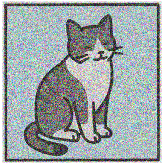
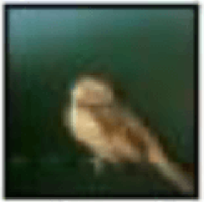
The required perturbation $\delta$ will be more and more perceptible by humans

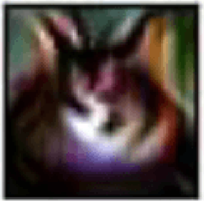


# Perceptually-Aligned Gradients

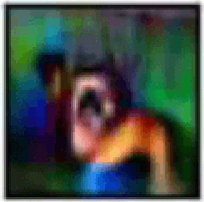

When our classifier has PAGs:



Original image: bird



A ”bird” classified as cat



A ”bird” classified as dog

**Gradients are aligned to the human perception**

Ganz et al, ”Do Perceptually Aligned Gradients Imply Robustness?”, 2023

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2 Inverse Language Modeling

# Attacking LLMs with GCG



Greedy Coordinate Gradient is an algorithm to find a sequence of tokens $\mathbf{x}_\star$ such that the LLM will complete with $\mathbf{y}$ that we want — using **gradients** on input tokens

| Input | Output $\mathbf{y}$ | Loss |
|---|---|---|
| $\mathbf{x}$ : Stevens recorded and produced the album at multiple<br>$\mathbf{x}_\star$: Zo Certified Cities (. broadcastquartered Fitness Academy thirteen | locations in the United | 5.3642<br>**5.1302** |
| $\mathbf{x}$ : After the introduction of the Majors , The<br>$\mathbf{x}_\star$: REQU Apart British received reformsMilitaryestic Division The | British Army was divided | 11.2146<br>**7.1899** |
| $\mathbf{x}$ : The founding director , Peggy Loar , left<br>$\mathbf{x}_\star$: tested UberERIC definitionCalifornia sustainability RutgersOL Jensen regarding | the University of California | 7.2669<br>**6.4402** |
| $\mathbf{x}$ : Ruiz notes that writing also has the power<br>$\mathbf{x}_\star$: Report Global feminism agenda Representatives tell Sacredixties Trying | to change the world | 5.9135<br>**4.6041** |

They are called ”Evil Twins”

# Difficulties of LLMs



What about LLMs?

- Input is **sequential**
- The same sequence can continue in multiple ways $\rightarrow$ **multiple** valid classes
- The input space is **discrete** ($|\mathcal{V}|$)

# Introducing ILM



- **Goal:** train LLMs to both generate text and *understand what they are conditioned on* **(inversion)** from the output
- **Key Ideas:**
  - Create a new training procedure that adds more **robustness** in the loop
  - Reconstruct input from the output, using $\nabla_{\mathbf{x}}\mathcal{L}$

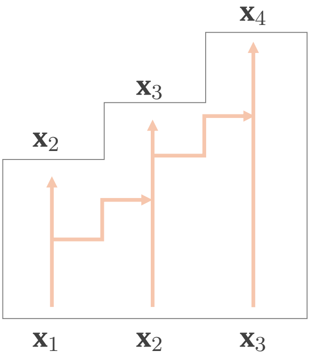
# Introducing ILM

## 2 Inverse Language Modeling

**Now**

Autoregressive forward

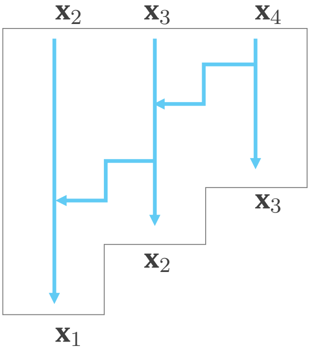
$$p(\mathbf{x}_i|\mathbf{x}_1,\ldots,\mathbf{x}_{i-1})$$




**Proposed**

Autoregressive backward

$$p\left(\mathbf{x}_{i-1}|\nabla_{\mathbf{x}_{i-1}}p(\mathbf{x}_i|\mathbf{x}_1,\ldots,\mathbf{x}_{i-1})\right)$$



Split it into the original prefix $\mathbf{x}_p = \mathbf{x}_{0:k}$ and the suffix $\mathbf{x}_s = \mathbf{x}_{k:n}$

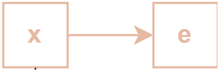
$\mathbf{x} =$ The pen is on the table

$\mathbf{x}_p =$ **The pen is** $\quad\quad$ $\mathbf{x}_s =$ on the table

*A causal model looks ahead,*
*but only its gradients disclose the pasts that might have built that future.*


Given the input sentence $\mathbf{x}_0, \mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_{n-1}$

# ILM Training Procedure

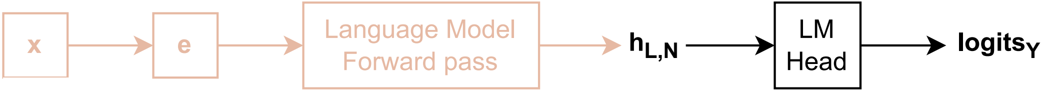




Embed the input sentence tokens into $\mathbf{e}_0, \mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_{n-1}$

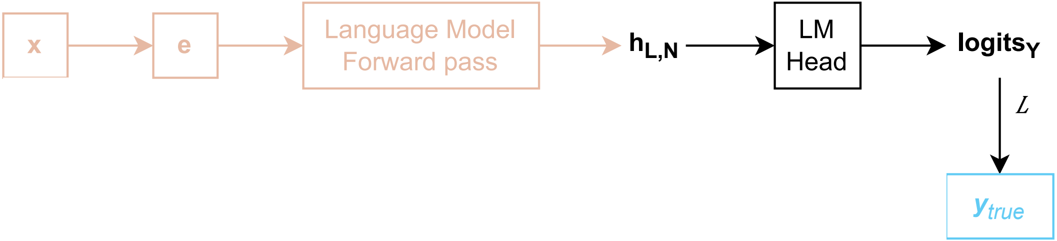
# ILM Training Procedure
## 2 Inverse Language Modeling


Pass through the Transformer Decoder layer, up to the final hidden state

$$\mathbf{h}_0, \mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_{n-1}$$



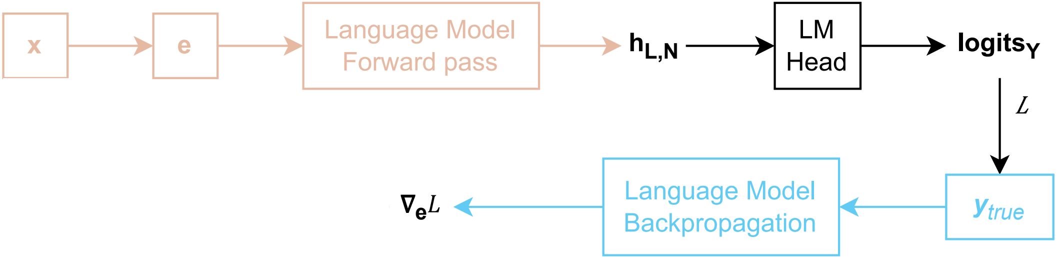

Using the Classifier Head, predict $\mathbf{y}_0, \mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_{n-1}$




Compute the loss $\mathcal{L}_{CE} = CE(\mathbf{x}_{1:n}, \mathbf{y}_{0:n-1})$ comparing the predictions with the ground-truth

# ILM Training Procedure

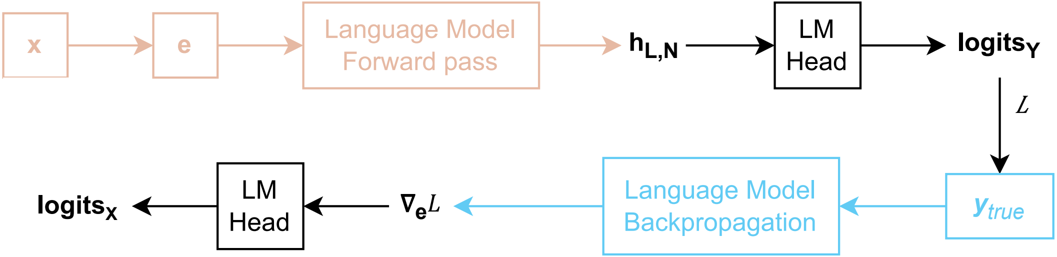





Backpropagation: compute the gradients $\nabla_{\mathbf{e}_{0:n-1}} \mathcal{L}$

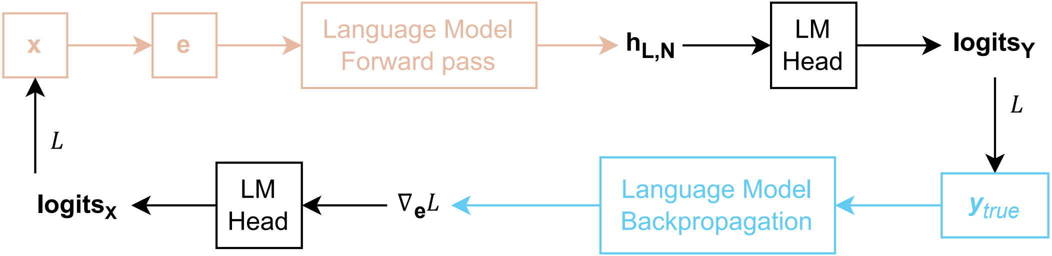
# ILM Training Procedure

## 2 Inverse Language Modeling




From the gradients, predict the input tokens $\mathbf{x}_{0:n-1}$

# Parallelism

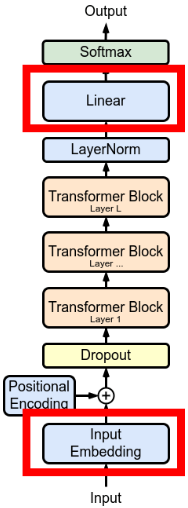



As if it were really **cyclic**!

Parallelism between the last hidden state and the gradients on the embeddings

# More Parallelism: Weight Tying





$$\mathcal{L} = \underbrace{\mathcal{L}_{CE}(\mathbf{y}_{\text{true}}, \mathbf{y}_{\text{pred}})}_{\text{Forward: from the input x, encode y}} + \underbrace{\lambda\, \mathcal{L}_{CE}(\mathbf{x}, f(\mathbf{x}, \nabla \mathbf{x}))}_{\text{Backward: from gradients, decode back x}}$$

# ILM Variants



$$\mathcal{L} = \underbrace{\mathcal{L}_{CE}(\mathbf{y}_{\text{true}}, \mathbf{y}_{\text{pred}})}_{\text{Forward: from the input x, encode y}} + \underbrace{\lambda\, \mathcal{L}_{CE}(\mathbf{x}, f(\mathbf{x}, \nabla\mathbf{x}))}_{\text{Backward: from gradients, decode back x}}$$

- **Identity**: what we have discussed so far

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**Classification Stategies:**

- Use gradient as **value** $-f(\nabla_{\mathbf{x}_i} \mathcal{L}_{CE})$

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**Classification Stategies:**

- Use gradient as **value** — $f(\nabla_{\mathbf{x}_i} \mathcal{L}_{CE})$
- Use gradient as **direction** — $f(\mathbf{x}_i - \nabla_{\mathbf{x}_i} \mathcal{L}_{CE})$

# But we don’t have billions of dollars



These results have been obtained on a tiny LLM:

- Only 10M parameters
- A vocabulary of just 2048 tokens
- A simple corpus (`TinyStories` dataset)

It will be scaled to Llama-1B in the future.

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# Inversion Evaluation



| | Grad. | Token Recall ↑ | Token Precision ↑ | Token F1-score ↑ | Positional Accuracy ↑ |
|---|---|---|---|---|---|
| Baseline | | 20.9% | 18.8% | 19.7% | 2.4% |
| Inv-First | Val. | 11.3% | 10.1% | 10.7% | 1.7% |
| Bert-like | Val. | 2.9% | 2.7% | 2.8% | 0.3% |
| Identity | Val. | 0.7% | 0.7% | 0.7% | 0.1% |
| Inv-First | Dir. | 13.3% | 12.0% | 12.6% | 2.4% |
| Bert-like | Dir. | 0.1% | 0.1% | 0.1% | 0.1% |
| **Identity** | Dir. | **22.5%** | **20.2%** | **21.2%** | **2.5%** |

Evaluation of the inversion capabilities, on metrics relative to the single tokens

# Inversion Evaluation



| | Grad. | Full Sentence Perplexity ↓ | Predicted Prefix Perplexity ↓ | Semantic Similarity ↑ |
|---|---|---|---|---|
| Baseline | | **8.34** | 112.82 | <u>0.28</u> |
| Inv-First | Val. | 10.21 | 1576.23 | 0.25 |
| Bert-like | Val. | 11.54 | 5501.86 | 0.17 |
| Identity | Val. | 13.88 | 14658.58 | 0.12 |
| Inv-First | Dir. | 9.77 | 1012.80 | **0.30** |
| Bert-like | Dir. | 11.05 | 563.26 | 0.11 |
| **Identity** | Dir. | **8.34** | **106.31** | **0.30** |

Metrics relative to the full sentences, computed using a third-party LLM

# Example of Inversion

## 3 Results

| | | |
|---|---|---|
| $\mathbf{x}$ | | dad in the garden. He gives her a small shovel and a bag of bulbs. |
| $\mathbf{x}_\star$ Baseline | | **to play with his cars, and look at the shake. She feels on her hand.** |
| $\mathbf{x}_\star$ Inv-First | (Val.) | zzle spowerlizza in her plate. She start to fence and leaves. |
| $\mathbf{x}_\star$ Bert-like | (Val.) | could buildDven measure its neighbign, how he sees nostiff. |
| $\mathbf{x}_\star$ Identity | (Val.) | Kugct propide,RallashQilndmawkeycessUuhingask do. |
| $\mathbf{x}_\star$ Inv-First | (Dir.) | too hurt the car's bricket. It did not want to grow in a cage. |
| $\mathbf{x}_\star$ Bert-like | (Dir.) | Tim! Tim,ide, Sue, Sue, Tim!ide, "Tim, "Tim,ice. Tim! Tim!ittenbbed Tim! Tim,ide,auseectle. |
| $\mathbf{x}_\star$ **Identity** | (Dir.) | **cars, and gets on his hand. But he does not want to play with the towers.** |
| $\mathbf{y}$ | | Bulbs are like round seeds that grow into flowers. Lily digs holes in the dirt and puts the bulbs inside. She covers them with more [...] |

## ILM Robustness Results



| | Grad. | GCG Success Rate ↓ | GCG Average Steps (mean ± stddev) |
|---|---|---|---|
| Baseline | | 95.9% | $277 \pm 148$ |
| Inv-First | | 85.0% | $320 \pm 134$ |
| Bert-like | Val. | **0.8%** | $249 \pm 148$ |
| Identity | | 88.1% | $274 \pm 145$ |
| Inv-First | | 89.3% | $313 \pm 134$ |
| Bert-like | Dir. | 85.5% | $287 \pm 143$ |
| **Identity** | | 82.8% | $284 \pm 141$ |

Identity looks good, but Bert-like is **suspicious**

# ILM Robustness — Metrics on the Model Itself



| | Grad. | Original X CE-loss ↓ | Attack X' CE-loss | Delta CE-loss ↓ | KL Divergence ↑ |
|---|---|---|---|---|---|
| Baseline | | 13.28 | 10.97 | 2.31 | 2.19 |
| Inv-First | Val. | **11.09** | 9.72 | 1.37 | 2.44 |
| Bert-like | Val. | 13.26 | 10.25 | 3.01 | **54.19** |
| Identity | Val. | 12.77 | 11.21 | 1.56 | 2.23 |
| Inv-First | Dir. | 11.21 | 9.81 | 1.40 | 2.44 |
| Bert-like | Dir. | 11.49 | 10.34 | **1.15** | 2.23 |
| **Identity** | Dir. | 12.58 | 11.12 | 1.46 | 2.47 |

Also, Bert-like seems to map $\mathbf{x}_\star$ to very different next token **distributions**

# ILM Robustness — Third-Party Model Metrics



| | Grad. | Original X Perplexity | Attack X' Perplexity ↓ | Semantic Similarity ↑ |
|---|---|---|---|---|
| Baseline | | 44.14 | 17344.04 | 0.13 |
| Inv-First | Val. | 44.81 | 9431.09 | 0.16 |
| Bert-like | Val. | 40.37 | 11817.21 | 0.11 |
| Identity | Val. | 43.98 | **8322.25** | **0.18** |
| Inv-First | Dir. | 43.50 | 12344.85 | 0.13 |
| Bert-like | Dir. | 44.74 | 10611.09 | 0.13 |
| **Identity** | Dir. | 44.71 | 10929.21 | 0.15 |

However, all $\mathbf{x}_\star$ are **meaningless**, due to extremely high perplexity

| | Input | Output y | Loss |
|---|---|---|---|
| $\mathbf{x}$ : | Lily and Ben were friends who liked to play outside. But they did not like the same things. Lily | liked to make snowmen and snow angel | 13.22 |
| $\mathbf{x}\star$: | Lucy. Speez herself angO piecle you.”lly named nexird opened cake”.o.ter carrotmy | | **12.14** |

An example result attacking with GCG the `Identity (grad. value)` model.
Almost the same for all model variants.

# Also on arXiv (2510.01929v1)

3 Results



## Inverse Language Modeling towards Robust and Grounded LLMs

Davide Gabrielli * [1] Simone Sestito * [1] Iacopo Masi [1]

*"A causal model looks ahead, but only its gradients disclose the pasts that might have built that future."*


### Abstract

The current landscape of defensive mechanisms for LLMs is fragmented and underdeveloped, unlike prior work on classifiers. To further promote adversarial robustness in LLMs, we propose Inverse Language Modeling (ILM), a unified framework that simultaneously 1) improves the robustness of LLMs to input perturbations, and, at the same time, 2) enables native grounding by inverting model outputs to identify potentially toxic or unsafe input triggers. ILM transforms LLMs from static generators into analyzable and robust systems, potentially helping RED teaming. ILM can lay the foundation for next-generation LLMs that are not only robust and grounded but also fundamentally more controllable and trustworthy. The code is publicly available at github.com/davegabe/pag-llm.


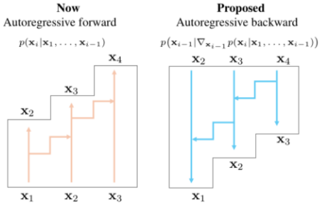


*Figure 1.* Illustration of Inverse Language Modeling (ILM) setup. Forward pass predicts next tokens, backward pass reconstructs inputs from gradients.

Efficient solutions for AT for LLMs intercept a pressing need (Xhonneux et al., 2024). In this work, we define **robustness** as reduced sensitivity to adversarially perturbed

# Inverse Language Modeling towards Robust and Grounded LLMs

*Thank you for listening!*
*Any questions?*