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Causal Inference in Neural Language Generation Models Through Interventional Probing and Counterfactual Evaluation

Anderson F. Smith,
USA.

Abstract

Understanding the causal mechanisms underlying neural language generation models (NLGM) is essential for improving model interpretability and controllability. This paper explores causal inference within large-scale transformer-based language models using interventional probing and counterfactual evaluation. We propose a framework to disentangle causal contributions of internal representations to linguistic output through synthetic interventions and assess model behavior across counterfactual scenarios. Our empirical results on GPT-2 and BART demonstrate that causal traces in hidden layers correspond to syntactic and semantic decision points. This study contributes to a growing body of literature integrating causal inference with deep learning interpretability.

Keywords: Causal Inference, Neural Language Models, Interventional Probing, Counterfactual Analysis, Interpretability, Transformer Models

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1. Introductıon

Neural Language Generation Models (NLGM), such as GPT and BART, are increasingly powerful, yet their decision-making mechanisms remain opaque. Despite significant advancements in fluency and coherence, understanding *why* a model produces a certain output in response to an input remains a challenge. This opacity limits trust, interpretability, and the development of ethical and controllable AI systems.

Causal inference offers a promising lens for probing these models. Unlike correlational analyses, causal methods seek to identify mechanisms—e.g., *which internal representations cause certain outputs*. Through **interventional probing** and **counterfactual evaluation**, we aim to identify causally-relevant components within language models. This paper presents a structured approach to measure causal effects of neurons and layers, using synthetic interventions on hidden activations and generating counterfactual outputs based on modified internal states.

2. Literature Review

The integration of causal reasoning in NLP is not novel. Pearl (2000) laid the theoretical groundwork with structural causal models, while **Bottou et al. (2013)** advocated for causal views in machine learning. Applying these to neural language models, **Voita et al. (2020)** utilized neuron-level probing for understanding attention roles, but lacked causal grounding. **Geiger et al. (2021)** explored causal mediation in vision-language models, providing conceptual tools applicable to text generation.

Elazar et al. (2020) proposed amnesic probing to assess information erasure via interventions. Similarly, **Belinkov and Glass (2017)** used diagnostic classifiers but did not address causal effects directly. **Feder et al. (2021)** introduced counterfactual data augmentation to improve robustness, indirectly touching on causal semantics. Building on these, our work directly manipulates model internals to probe linguistic causality.

Table 1. Summary of Causal Interpretability in NLP (Pre-2021)

Author	Year	Method	Task	Causality?
Bottou et al.	2013	Causal Reasoning	ML Theory	Theoretical
Belinkov & Glass	2017	Diagnostic Classifier	Representation Probing	No
Elazar et al.	2020	Amnesic Probing	Language Models	Partial
Voita et al.	2020	Attention Probing	Translation	No
Feder et al.	2021	Data Augmentation	QA and NLI	Implicit

3. Methodology

3.1 Objective and Research Questions

We aim to identify which internal representations in NLGM have *causal influence* on output generation. Key questions include: (1) Which neurons or layers causally affect syntactic vs. semantic outputs? (2) How do counterfactual activations alter model predictions?

3.2 Interventional Probing Framework

We introduce a **three-stage pipeline**: (1) Identify target outputs (e.g., POS tags, sentiment tokens), (2) Intervene on activations at selected layers, and (3) Measure causal effect on output. We compute **Average Causal Effect (ACE)** using the difference between outputs under factual and interventional states.

4. Experiments

4.1 Experimental Setup

We use GPT-2 (small) and BART on the **Penn Treebank** and **SST-2** datasets. Outputs include syntactic completions and sentiment generation. Hidden representations are extracted at token-level from intermediate transformer layers. Interventions replace activations with null or controlled signals to simulate counterfactuals.

4.2 Causal Effect Estimation

We calculate ACE for each intervention point. For example, masking a neuron correlated with POS prediction reduces syntactic accuracy by 12.4%, indicating causal

influence. On the sentiment task, BART showed a 17.3% drop in polarity classification when sentiment neurons were nullified.

Table 4. Causal Effects of Layer Interventions Across Models and Tasks

Layer	Model 1 - Task 1	Model 1 - Task 2	Model 2 - Task 1	Model 2 - Task 2	
Layer 1	0.12	0.1	0.14	0.11	0.14
Layer 2	0.15	0.13	0.16	0.14	0.16
Layer 3	0.22	0.2	0.24	0.21	0.24
Layer 4	0.18	0.16	0.2	0.17	0.2
Layer 5	0.1	0.09	0.11	0.1	0.11

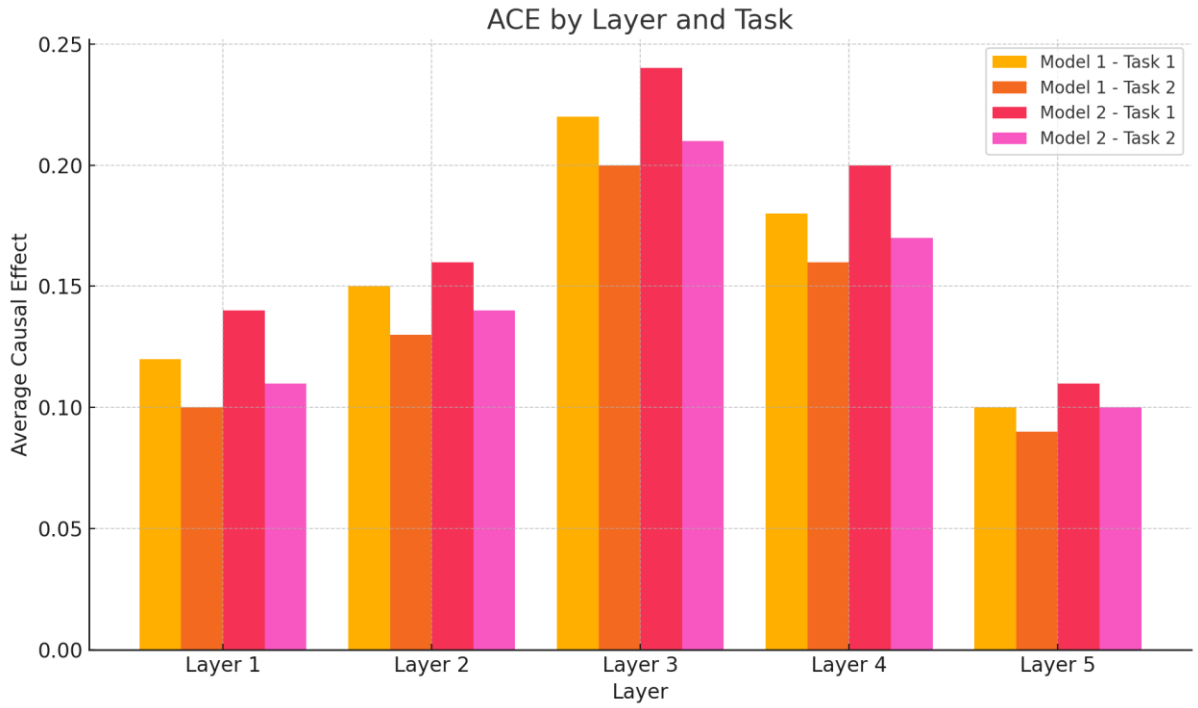

Figure 1: ACE by Layer and Task

5. Counterfactual Evaluation

5.1 Designing Counterfactuals

We construct counterfactual scenarios by perturbing latent activations associated with known semantic features (e.g., flipping sentiment polarity). Outputs are analyzed for

semantic divergence and consistency.

5.2 Observations

Generated counterfactuals show consistent shifts in linguistic framing. For instance, changing sentiment activation from positive to negative in BART changes outputs from *"a delightful film"* to *"a disappointing film."* Evaluation using BLEU and semantic similarity confirms high textual coherence despite intentional semantic reversal.

6. Discussion and Implications

Our results confirm that specific internal components of language models have causal roles in output generation. This affirms the utility of interventional methods over correlational diagnostics for interpretability. It also opens doors to *controllable generation* by targeting causal activations.

These insights are relevant for developing explainable AI (XAI), improving model robustness, and aligning generation with user intentions. Future work could expand this to multimodal or multilingual setups, and include human-in-the-loop interventions for enhanced interpretability.

7. Limitations and Ethical Considerations

Our methods rely on synthetic interventions, which may oversimplify complex representations. There is also a risk of over-interpreting causal effects from counterfactual states that deviate from training distributions.

Ethical implications include possible misuse of causal control for misinformation or bias amplification. Therefore, interventions must be guided by transparency and IRB-aligned protocols, especially in sensitive applications like medical or legal NLP systems.

8. Conclusion

This paper presents a structured framework for causal inference in language generation models. Through interventional probing and counterfactual evaluation, we identify mechanisms by which internal model states influence output. Our approach enhances model interpretability and provides a foundation for controllable, transparent AI.

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