Comparing Rule-Based NLG (Reiter & Dale) vs. GPT-Type Models: A Research Summary for Aspiring Scientists

August 4, 2025

1 Introduction

This document compares early rule-based Natural Language Generation (NLG) systems, as described by Ehud Reiter and Robert Dale, with modern GPT-type models. Aimed at aspiring scientists, it provides a beginner-friendly analysis of capabilities, design philosophies, and research directions in NLG. The goal is to equip you with a clear understanding of NLG's evolution and inspire research ideas for your scientific career.

2 What is NLG?

Natural Language Generation (NLG) is an AI subfield that generates human-like text from non-linguistic data, such as numbers or databases. For example, from data like {temperature: 25, condition: sunny}, an NLG system might produce: "It's a sunny day with a temperature of 25řC." As a scientist, NLG is valuable for communicating complex data, automating reports, and exploring AI's creative potential.

3 Rule-Based NLG vs. GPT-Type Models

3.1 Overview

- **Rule-Based NLG (Reiter & Dale)**: Developed in the 1990s–2000s, these systems use human-crafted templates and rules to generate text. Key work: Reiter and Dale's *Building Natural Language Generation Systems* (2000), which formalized the NLG pipeline (data input $\rightarrow$ content planning $\rightarrow$ sentence planning $\rightarrow$ realization).
- **GPT-Type Models**: Modern neural NLG systems based on Transformers, like GPT-2 and GPT-3, developed by OpenAI. They use large-scale neural networks trained on vast text datasets to generate flexible, context-aware text.

Aspect	Rule-Based NLG	GPT-Type Models
Text Quality	Predictable, accurate for structured data, but rigid (e.g., “The temperature is 25řC.”)	Fluent, creative, human-like (e.g., “Expect a warm, sunny day at 25řC.”)
Flexibility	Limited to templates; struggles with creative tasks	Highly flexible; handles stories, dialogue, summaries
Scalability	Scales for specific tasks but requires new rules for new domains	Scales to diverse tasks via fine-tuning, but resource-heavy
Data Requirements	Needs structured data and expert rules	Needs massive text corpora; fine-tuning requires less data
Error Handling	Robust for known inputs; fails with unexpected data	Can hallucinate but handles diverse inputs better
Applications	Narrow (e.g., weather reports, financial summaries)	Broad (e.g., chatbots, creative writing)

Table 1: Comparison of Rule-Based NLG and GPT-Type Models

3.2 Capability Comparison

3.3 Design Philosophy Comparison

- **Rule-Based NLG**:
  - *Top-Down, Knowledge-Driven*: Relies on expert-crafted rules and templates. The NLG pipeline is explicitly designed.
  - *High Control*: Predictable and transparent outputs, easy to debug.
  - *Development*: Time-intensive, requiring domain expertise.
  - *Philosophy*: Prioritizes precision and domain-specific accuracy (“Engineer the system to fit the task”).
- **GPT-Type Models**:
  - *Bottom-Up, Data-Driven*: Learns patterns from large datasets with minimal human rules.
  - *Low Control*: Probabilistic outputs, less predictable, hard to debug.
  - *Development*: Requires computational resources; adaptable via fine-tuning.
  - *Philosophy*: Emphasizes generalization and versatility (“Let the model learn from data”).

4 The Shift in NLG

4.1 From Rigid to Flexible

Rule-based systems were limited to specific tasks (e.g., weather reports) due to fixed templates. GPT models generate text across domains, from poetry to technical reports, but risk hallucination (generating false information).

4.2 From Expert-Driven to Data-Driven

Rule-based NLG required experts to design rules, making it interpretable but labor-intensive. GPT models learn from vast datasets, reducing manual effort but introducing bias and transparency challenges.

4.3 From Narrow to Broad Applications

Rule-based systems were confined to structured domains. GPT models enable NLG in creative and open-ended tasks, expanding its reach to chatbots, education, and more.

4.4 From Transparent to Black-Box

Rule-based systems are transparent, with outputs traceable to rules. GPT models are black-box, making it hard to understand decision-making, prompting research into explainable AI.

5 Rare Insights for Researchers

- **Hallucination in GPT**: Neural models may generate plausible but false text (e.g., “25řC in Antarctica”). Researching hallucination detection is critical.
- **Contextual Nuances**: GPT struggles with cultural or domain-specific nuances (e.g., medical terminology). Domain adaptation is a growing field.
- **Energy Efficiency**: Rule-based systems were lightweight; GPT models are resource-intensive. Green NLG is an emerging research area.
- **Hybrid Approaches**: Combining rule-based precision with neural flexibility (e.g., using templates to constrain GPT outputs) is a promising direction.

6 Research Directions

As an aspiring scientist, consider these areas:

- **Hybrid Systems**: Integrate rule-based and neural NLG for controlled yet flexible outputs.
- **Explainable NLG**: Develop methods to make GPT models transparent, inspired by rule-based systems.
- **Bias Mitigation**: Address biases in GPT training data using rule-based checks.

- **Domain Adaptation**: Fine-tune GPT for niche domains like scientific writing.
- **Green NLG**: Create energy-efficient NLG models.
- **Evaluation Metrics**: Design metrics to better capture fluency and context.

7 Next Steps for Aspiring Scientists

- **Read**: Study Reiter & Dales *Building Natural Language Generation Systems* (2000) and the GPT-3 paper (Brown et al., 2020).
- **Experiment**: Build a rule-based NLG system (e.g., CSV to text) and compare with a fine-tuned GPT model.
- **Research**: Explore hybrid NLG systems or hallucination detection.
- **Collaborate**: Join AI communities on platforms like X or GitHub.
- **Publish**: Share findings in journals or online to contribute to NLG research.

8 Conclusion

The shift from rule-based NLG to GPT-type models marks a transition from rigid, expert-driven systems to flexible, data-driven ones. While rule-based systems offer control and transparency, GPT models excel in creativity and versatility. As a scientist, you can bridge these paradigms by researching hybrid systems, explainability, and ethical NLG. This summary provides a foundation to explore NLGs past, present, and future, guiding your scientific journey.