




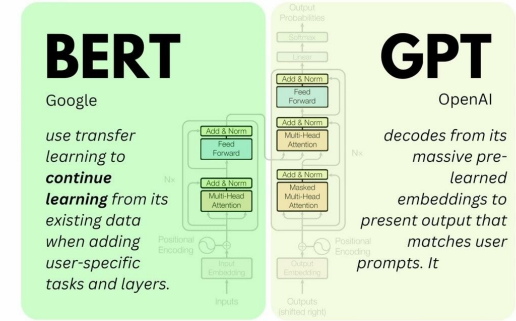
# **Can Foundation Models Talk Causality?**

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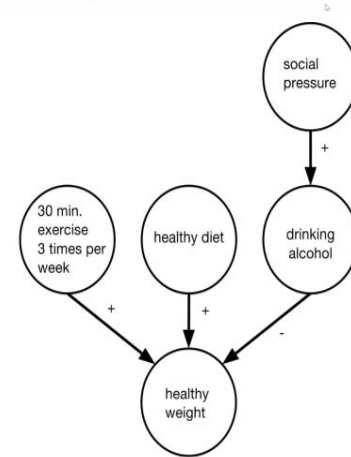
# Executive Summary

- Investigates foundation models in NLP, focusing on causal understanding.
- Explores BERT and GPT's ability to comprehend causality.
- Conducts experiments to test models on cause-effect tasks.
- Provides insights into strengths and limitations of foundation models.
- Highlights impressive performance on certain tasks but identifies gaps in understanding.
- Discusses implications for NLP advancement and the need for further research.
- Contributes to understanding foundation models' processing of causal information.



Current guidelines suggest a healthy diet, and a minimum of 30 minutes of physical activity 3 times per week is needed to maintain a healthy weight. Social pressure may have a negative impact on weight by increasing the consumption of alcohol, which can lead to weight gain.

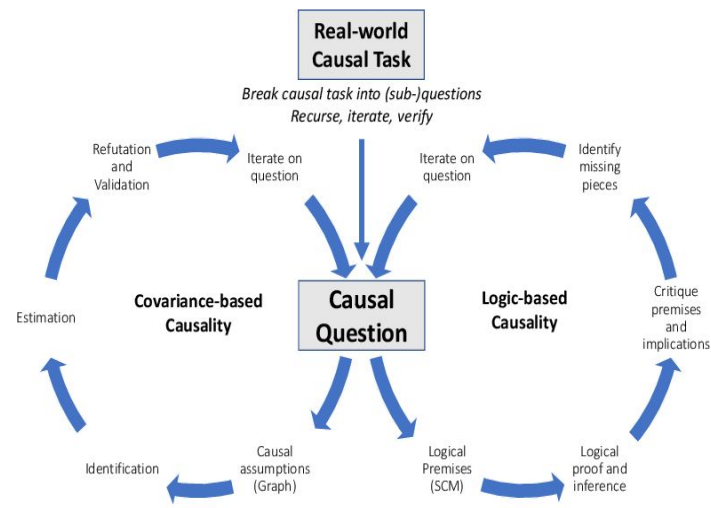
(a) Text-based causal information



(b) Causal diagram

# Background

- Rise of advanced language models like BERT and GPT for language processing tasks.
- Models excel in tasks such as translation and sentiment analysis.
- Challenge lies in understanding cause-and-effect relationships in text.
- Humans intuitively grasp causal connections, but it's challenging for machines.
- Causal reasoning is complex and involves understanding the reasons behind events.
- Traditional methods manually feed machines rules or knowledge bases for causal reasoning.
- Large-scale models offer an opportunity for machines to learn causal reasoning from data.
- Research aims to evaluate models' capabilities and limitations in understanding cause-and-effect relationships in text.



**Counterfactual:** Structural Causal Models, Counterfactual Models, Identification and Inference.

**Interventional:** Causal Discovery, Causal Identification and Causal Inference.

**Associational:** Structure Learning, Bayesian Networks and Bayesian Network Inference.

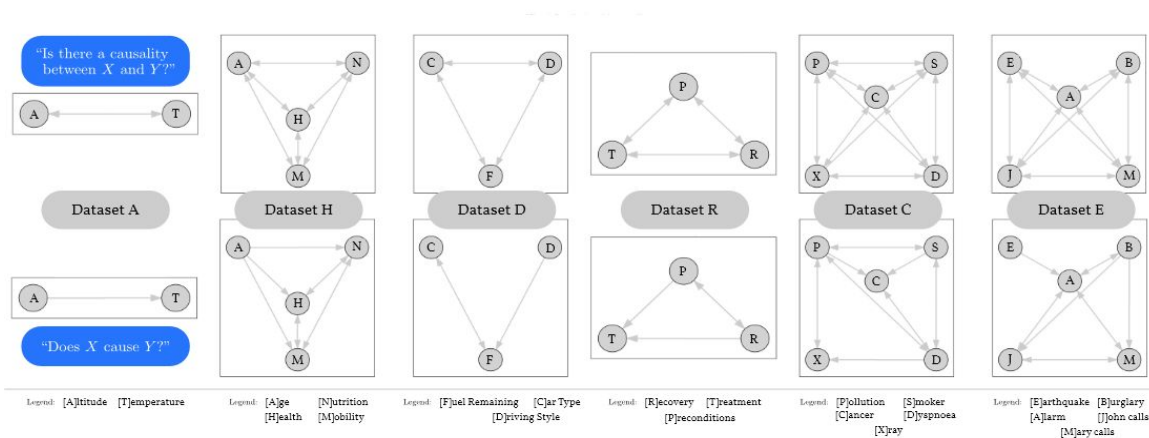
# Experiments and Results

- Design of experiments testing models' understanding of causal relationships in text.
- Examples of experimental scenarios and tasks presented to the models.
- Mixed results indicating strengths and weaknesses in models' causal reasoning abilities.
- Implications for advancing language comprehension in AI systems.

**Q1** How do the FM graph predictions compare to settings where the causal graph is (partially) known?

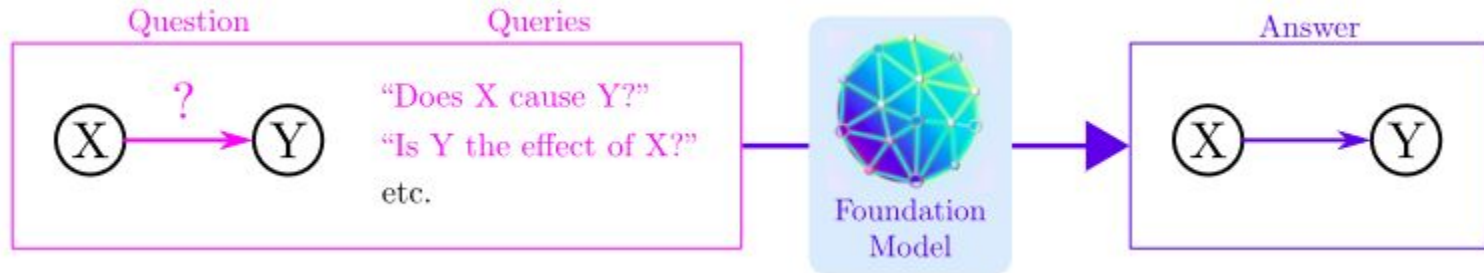
**Q2** How do the FM graph predictions perform in “common sense” settings that involve abstract reasoning and intuitive physics?

**Q3** How do synonyms or more general variable name alterations affect the FM graph prediction?

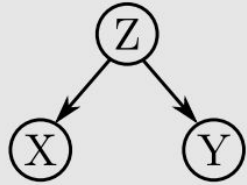


# Methodology

- Systematic approach to investigating causal reasoning in language models.
- Curation of diverse dataset and crafting of experimental tasks.
- Rigorous evaluation metrics and procedures ensuring validity and reliability.
- Advanced statistical analysis techniques applied for insights.



## Causal Assumptions



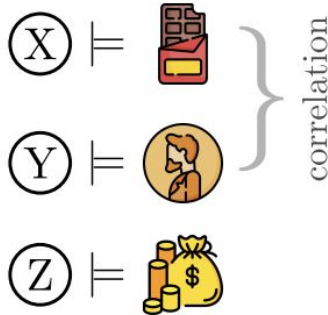
“Z is common cause of X and Y”

“X and Y are causally unrelated”

## Classical Setting

Variables model natural concepts

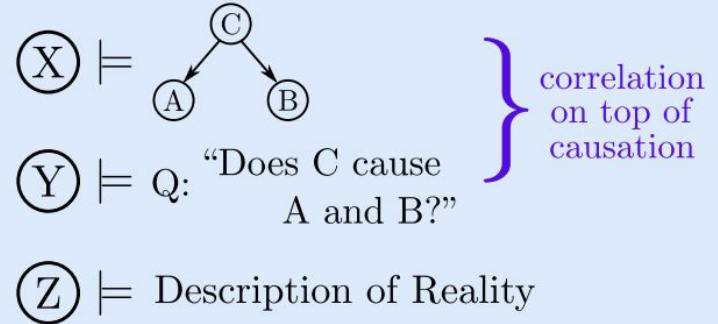
Example:






## Meta-level Setting

Variables model causal assumptions

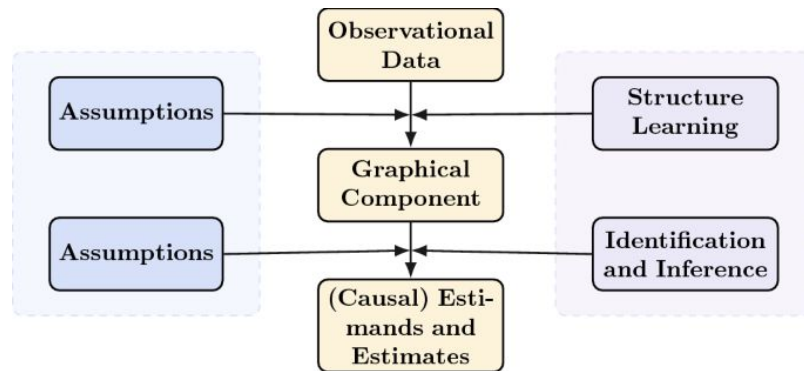
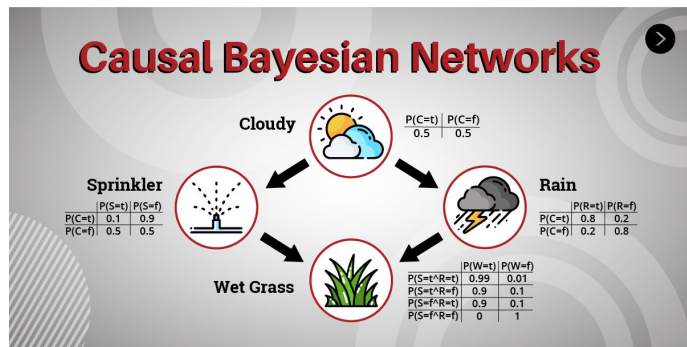
Example:



Legend:  “Chocolate Consumption”  “Number of Nobel Laureates”  “Gross Domestic Product (GDP)”

# Key Findings

- Nuanced understanding of causal relationships demonstrated by models.
- Contextual sensitivity aiding accurate causal inference.
- Generalization of causal reasoning abilities across domains.
- Limitations observed in counterfactual reasoning.
- Implications for natural language understanding and future research directions.



# Discussion Points

- Depth of interpretative understanding versus surface-level associations.
- Role of context in facilitating accurate causal inference.
- Challenges in counterfactual reasoning and manipulation of causal variables.
- Generalizability of causal reasoning abilities across diverse domains.
- Broader implications for AI development and ethical considerations.



# Limitations and Open Points

- Scope limitations concerning textual genres and domains analyzed.
- Challenges related to data availability and quality for training causal reasoning models.
- Need for robust evaluation metrics capturing complexities of causal inference.
- Importance of interpretable model architectures for transparent causal reasoning.
- Ethical and societal implications of deploying advanced causal reasoning models in real-world applications.

Any Questions?