



Reflexive Evidence-Based Multimodal Learning for Clean Energy Transitions: Causal Insights on Cooking Fuel Access, Urbanization, and Carbon Emissionss



Shan Shan

Zhejiang University

Advancing Evidence-Based AI Policy for Climate Change

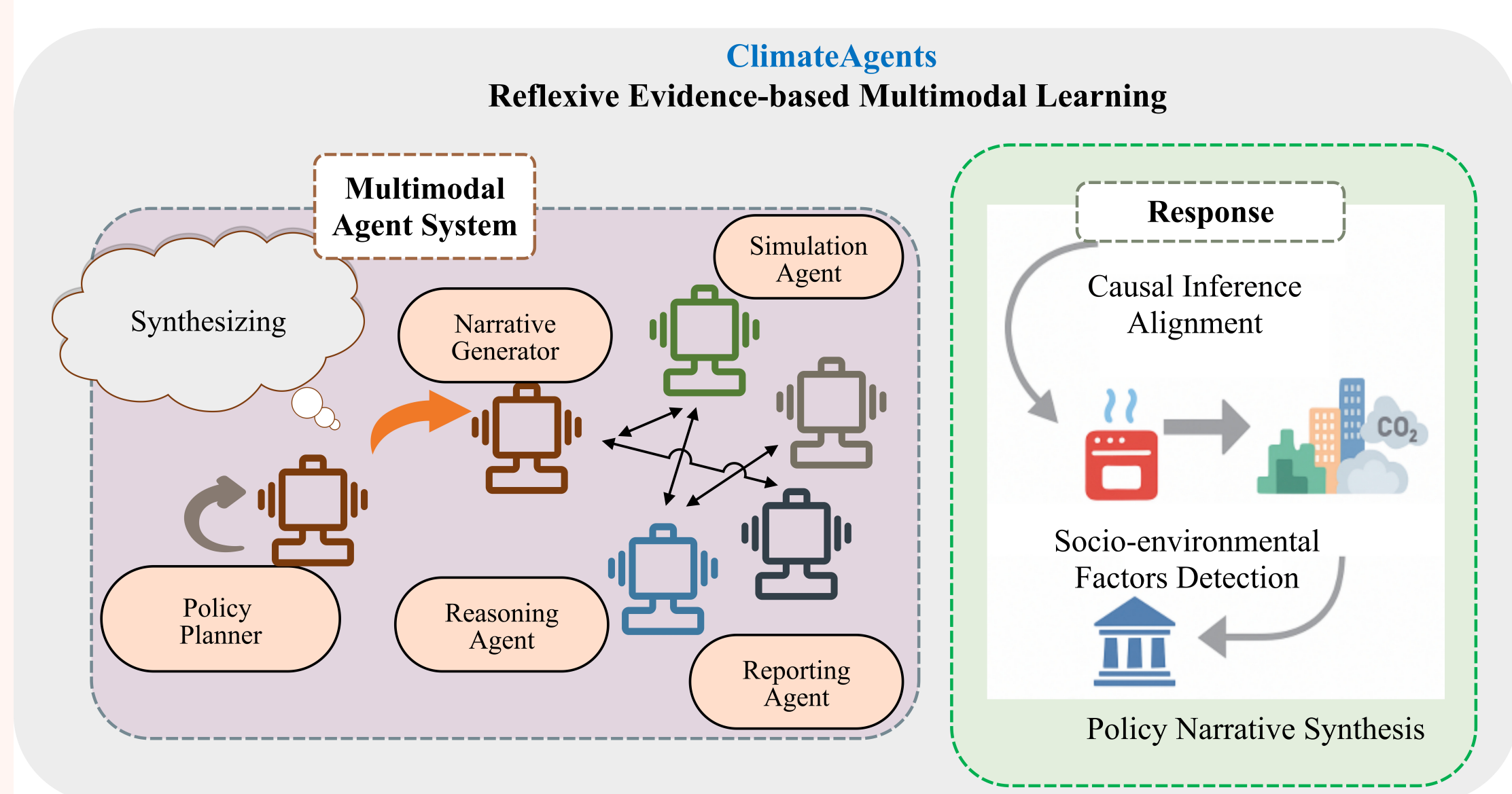
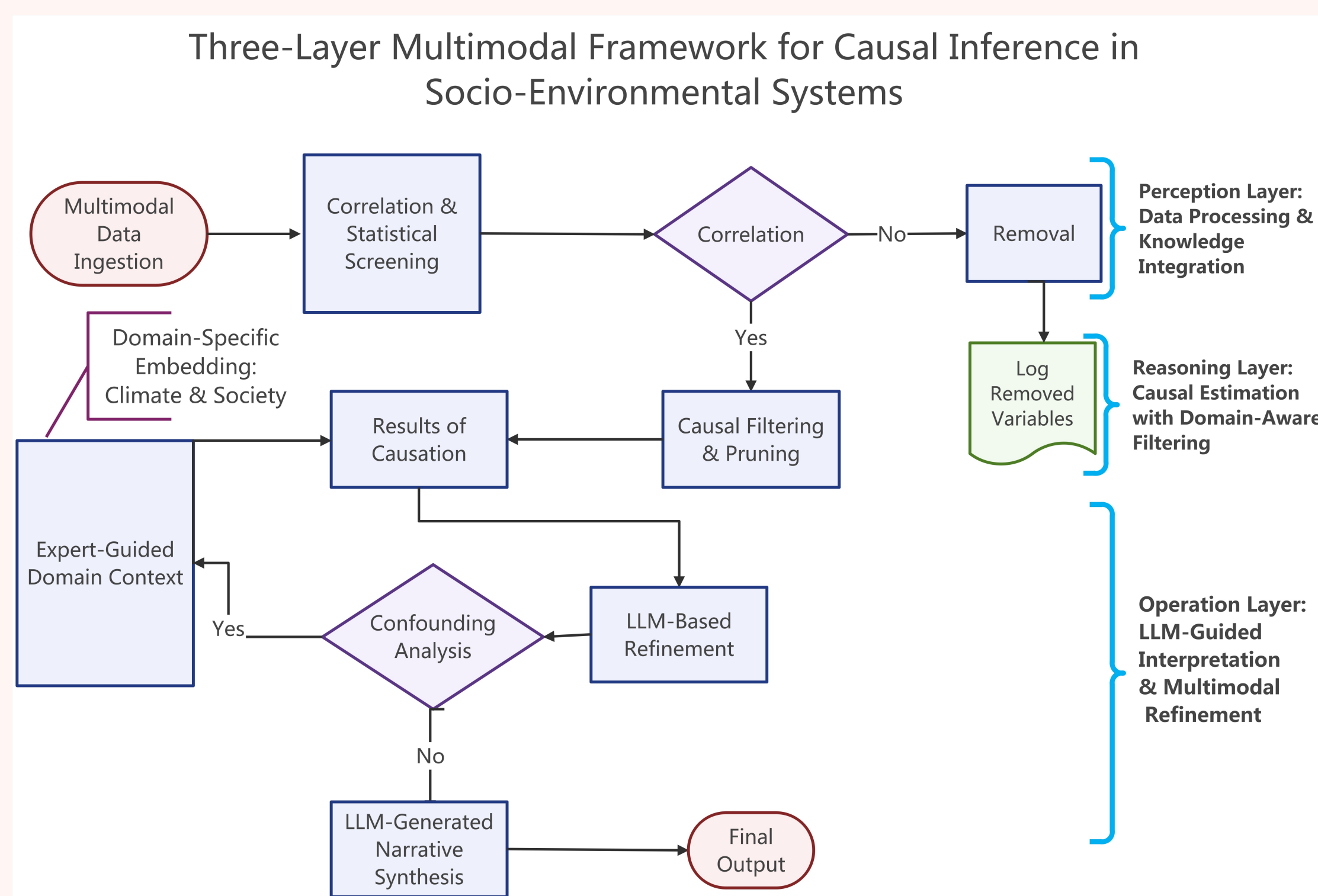
- Achieving **SDG 7 (Affordable and Clean Energy)** requires understanding not only technology gaps but also **socio-economic drivers** of energy access and emissions.
- A key challenge in the social sciences is to design systems that support **adaptive intelligence** by integrating diverse knowledge, tools, and automated modeling.
- How can narrow AI components be unified into a context-aware agent that:
 - processing multimodal data,
 - reasoning causally,
 - interacting socially,
 - adapting continuously to evolving policy challenges.

- Goal:** Advancing Evidence-Based AI Policy for Climate Change

- Solution:** **ClimateAgents** is a reflexive multimodal AI framework using LLMs and domain agents for causal reasoning on clean energy transitions

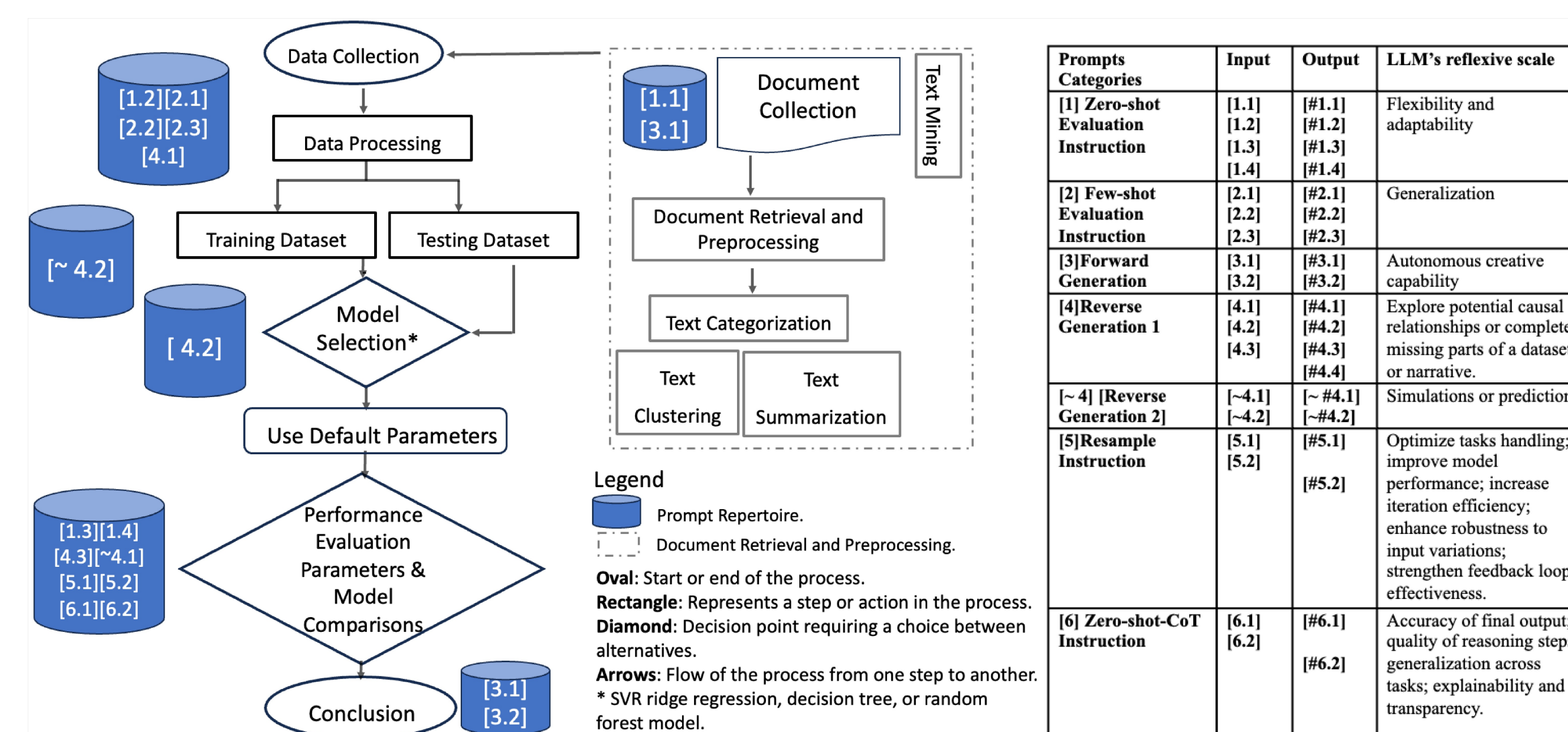
ClimateAgents

- Credible and actionable:** Leveraging 20 years of socio-economic and emissions data covering 265 economies, countries and regions across 98 indicators, the framework applies a machine learning-based causal inference approach to identify key determinants of carbon emissions.



Perception Layer: Knowledge Retrieval

Data Processing & Knowledge Integration. The correlation step uses a heatmap and the Anderson-Darling K-sample test (threshold: 0.1) to identify variables influencing carbon emissions. Variables with matching training and testing distributions are retained for causation analysis.



Prompt Categories	Input	Output	LLM's reflexive scale
[1] Zero-shot Evaluation Instruction	[1.1] [1.2] [1.3] [1.4]	[#1.1] [#1.2] [#1.3] [#1.4]	Flexibility and adaptability
[2] Few-shot Evaluation Instruction	[2.1] [2.2] [2.3]	[#2.1] [#2.2] [#2.3]	Generalization
[3] Forward Generation	[3.1] [3.2]	[#3.1] [#3.2]	Autonomous creative capability
[4] Reverse Generation 1	[4.1] [4.2] [4.3]	[#4.1] [#4.2] [#4.3]	Explore potential causal relationships or complete missing parts of a dataset or narrative
[~4] [Reverse Generation 2]	[~4.1] [~4.2]	[~#4.1] [~#4.2]	Simulations or prediction
[5] Resample Instruction	[5.1] [5.2]	[#5.1] [#5.2]	Optimize tasks handling; improve model performance; increase iteration efficiency; enhance robustness to input variations; strengthen feedback loop effectiveness.
[6] Zero-shot-CoT Instruction	[6.1] [6.2]	[#6.1] [#6.2]	Accuracy of final output; quality of reasoning steps; generalization across tasks; explainability and transparency.

Reasoning Layer: Causal Effects

- Dataset:** Selected variables $\{X_1, \dots, X_{16}\} = \{V^{2000}, Y^{2005}\}$ modeled as:

$$X_i = f_i(\text{pa}_i(X)) + \epsilon_i, \quad p(x) = \prod_i p(x_i | \text{pa}_i(x))$$

where $\text{pa}_i(X)$ are parents, and ϵ_i is additive noise.

- Score Function:** Defined as $s(x) = \nabla \log p(x)$. A variable X_j is a leaf node if:

$$\text{Var}_X \left(\frac{\partial s_j}{\partial x_j} \right) = 0, \quad \text{Var}_X \left(\frac{\partial s_j}{\partial x_i} \right) \neq 0 \text{ for parent } X_i$$

Leaf nodes are removed iteratively using Stein gradient estimator with RBF kernel to estimate Jacobian (Rolland et al., 2022).

- CAM Pruning:** Refines causal structure by eliminating spurious links:

- Structural:** SID, SHD
- Predictive:** Precision, Recall, F1 score
- Deviation:** L2 distance

	EG.CFT.ACCS.RU.ZS	EG.CFT.ACCS.RU.ZS	EG.CFT.ACCS.RU.ZS	EG.CFT.ACCS.RU.ZS	EG.CFT.ACCS.RU.ZS	SP.URB.TOTL	SP.URB.TOTL	SP.URB.TOTL	SE.SEC.DURS	EG.FEC.RNEW.ZS	SP.URB.TOTL	SP.URB.TOTL	AG.LND.FRST.ZS	ER.FSHCAP.TMT	CO2
EG.CFT.ACCS.RU.ZS	0	0	0	0	0	0	0	0	3	0	0	4	0	0	0
EG.CFT.ACCS.RU.ZS	0	0	4	0	0	2	2	0	0	0	0	4	0	0	2
EG.CFT.ACCS.RU.ZS	0	0	0	0	0	0	1	0	0	0	1	4	0	0	1
EG.CFT.ACCS.RU.ZS	0	4	0	0	0	2	0	0	0	0	1	4	0	0	0
EG.CFT.ACCS.RU.ZS	0	1	0	3	0	4	0	0	1	0	0	0	0	0	0
SP.URB.TOTL	0	2	0	1	0	0	1	0	4	0	4	1	0	0	0
SP.URB.TOTL	0	0	1	0	1	0	0	0	0	0	0	0	0	0	4
SP.URB.TOTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SE.SEC.DURS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EG.FEC.RNEW.ZS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP.URB.TOTL	0	0	0	0	0	0	0	0	1	0	0	0	0	2	0
SP.URB.TOTL	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
AG.LND.FRST.ZS	0	2	0	0	1	1	4	0	0	0	0	0	0	0	0
ER.FSHCAP.TMT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CO2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Operation Layer: Validation and Interpretation

- Rural Clean Fuel Access (EG.CFT.ACCS.RU.ZS):** Greater access in rural areas significantly lowers emissions, underscoring its role in climate mitigation.
- Urban Clean Fuel Access (EG.CFT.ACCS.UR.ZS):** Essential for emission reductions in high-density regions; a critical focus for urban policy.
- Urbanization (SP.URB.TOTL.IN.ZS):** Rising urban populations increase energy use and emissions, highlighting the need for sustainable urban development.

User: Rural areas (EG.CFT.ACCS.RU.ZS) have lower access to clean fuels than urban ones (EG.CFT.ACCS.UR.ZS), and urbanization (SP.URB.TOTL.IN.ZS) is increasing. Could variability in clean fuel access affect the effectiveness of environmental policies at reducing emissions?

AI Social-Scientist (GPT): Policy Effectiveness: Greater variability weakens uniform outcomes. **Emission Impact:** Urban-focused policies may yield quick results, but lasting success requires rural inclusion. **Urbanization Factor:** Shifts where and how policies work; less urbanized regions need tailored approaches. **Policy Design:** Reducing variability can support equitable and impactful strategies.

Summary and Future Perspectives

Data Processing

The study examines per capita CO₂ emissions using data from 265 economies, countries and regions across 2000–2020. Variables cover emissions, energy use, economic development, education, and urbanization, sourced from the World Bank.

Taxonomy of Causality

Five types of causal relationships that verbs can imply: Direct, Preventative, Facilitative, Resultative, and Influential.

Three Steps Causal Analysis Framework

Correlation analysis helps narrow down and identify connections, causality provides a stricter and more precise understanding of these relationships, and LLMs interpret the results within specific scenarios.

Future Research

With more data and a deeper grounding in real-world societal settings, studies on vertical domains could be expanded on a larger scale and have a more profound impact on policymaking.

Acknowledgement

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Reference: Rolland, P., V. Cevher, M. Kleindessner, C. Russell, D. Janzing, B. Schölkopf, and F. Locatello (2022). Score matching enables causal discovery of nonlinear additive noise models. Shan, S. (2024). From correlation to causation: Understanding climate change through causal analysis and LLM interpretations.

