Algorithmic Information Dynamics of Climate Risk in Supply Chain Management

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Introduction

As Earth's collective data sets become increasingly comprehensive and granular, it makes sense to leverage advanced GIS techniques, complexity science, and artificial intelligence to enable organizations to become highly adaptable in light of climatological and geopolitical volatility. With modern technology, infrastructure projects are capable of being architecturally rendered with unprecedented rapidity and new techniques from emergent sciences can be deployed to augment our existing strategic corporate communications and real-time analytic capabilities to capitalize on what that could mean for the future of international supply chains.

Method

We propose the incorporation of cutting-edge techniques from the theory of complex adaptive systems to identify logistical bottlenecks in global manufacturing, assess climate risk to international supply chains, and prescribe financially viable adjustments that are robust to climate change. Working off the insight that economic systems are a form of collective computation, we use algorithmic information dynamics to quantify causal information flow in an organization's supply chain and meta-reinforcement learning to train agents to use this.

Algorithmic information dynamics (AID) is a probabilistic framework for generating causal models (Zenil et al. 2018). Unlike the more commonly known Bayesian methods, AID does not require graphical models or classical probability distributions based on prior knowledge.

Instead, it merges the latest research in algorithmic logic, causal inference, information theory, nonlinear dynamical systems, and stochastic processes to systematically mine and generate mechanistic models for natural phenomena, including the impact of climate change on the flow of goods and services in international supply chains.

In particular, we've decomposed a firm's manufacturing process into a directed acyclic graph in order to identify vulnerabilities and inefficiencies in the various stages ranging from sourcing, production, warehousing, transportation, point-of-sale, and consumer. In order to explore the effects of climate change on this process, we carry out algorithmic intervention analysis to automate the discovery of primary causal computable models and pinpoint the causal effects of climatological perturbations on these underlying computable models. Algorithmic information analysis, an active area of mathematical research, supplements conventional techniques in causal inference such as Judea Pearl's

(2009) do-calculus or Granger causality (1969) which assume an a priori causal model. Instead, AID generates numerous computable models ranked by likelihood and completely substitutes correlation in the model's description, removing the statistical nature of the model by conducting both interventions and assessing counterfactuals for all possible computable hypotheses up to the length of the original observation. Thus, as we incorporate more climatological data, we will generate mechanistic models with greater accuracy and precision.

Simultaneously, we have used meta-reinforcement learning to train agents that exploit these causal models in order to maximize profit despite climate change. Inspired by Dasgupta's (2019) work at DeepMind, we have trained a recurrent neural network with model-free reinforcement learning to quantify climate risk in a given supply chain and propose alternative infrastructural topologies and geometries that maximize expected profit in light of rising sea levels, rising temperatures, and extreme weather events. We used ArcGIS to explore climate projections in the near future and ground our suggestions in light of geopolitical, trade, and cultural relations (Amman et al. 2018). Our methodology is computable, scalable, and generalizable. Thus, it can be applied independent of scale. As case studies, we have chosen to investigate climate risk in agriculture, as food supply has always been central to scaling civilizations.

Prospective Results, Discussion and Future Directions

This initial foray represents one set of techniques extracted from the sciences of complexity mapped to one set of issues arising in industrial activity and cartographic expertise (i.e. supply chain). We are preparing ensuing articles and explorations to explore and integrate more of these techniques into emergent tools, technologies, spatial algorithms and industrial solutions in the GIS space. There are numerous global supply chains at risk for disruption. The risks come not only from natural disasters, but also breakdowns in critical infrastructure, geographic shifts in resource availability and volatility in international trade. Organizations must reframe their idea of adaptation from a one-time effort to a proactive and iterative process. Doing this right requires conducting a detailed review of all the potential risks to your enterprise from physical climate risk, then leveraging modern computation techniques to generate insights with AI and present the supply chain in easily accessible visual interfaces. The time is right for this kind of work, and we are ready and willing to assist and meaningfully contribute.

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