TA

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AI in agriculture

Precision Farming

Crop Monitoring and Disease Detection

Yield Prediction

Automated Harvesting and Weed Control

Livestock Health Monitoring

Soil and Crop Health Analysis

AI in agriculture

Water Management

Weather Forecasting

Supply Chain and Market Optimization

Plant Breeding and Research

Emerging Trends

Drone-Assisted Aerial Surveillance: Drones equipped with AI analyze crop health and autonomously apply treatments only where needed, improving both efficiency and environmental outcomes.

Generative AI for Scenario Planning: Advanced AI models synthesize vast datasets (weather, soil, pest pressure) to generate scenarios for risk management and strategic planning, further optimizing farm operations.

Major AI Safety Subdomains

Robustness

Interpretability (Explainability)

Reward Learning (Value Alignment)

Monitoring and Oversight

Ethical and Societal Risks

Cybersecurity and Adversarial AI

Policy, Governance, and Norms

AI safety summary

Subdomain	Focus Area
Robustness	Reliable performance, adversarial resistance, fault tolerance
Interpretability	Transparency, explainability, bias detection
Reward Learning	Value alignment, safe objective specification
Monitoring	Ongoing oversight, anomaly detection, intervention
Ethics	Fairness, privacy, societal impact
Cybersecurity	Protection against attacks, adversarial robustness
Governance	Policy, standards, regulatory frameworks

AI Heuristics Study

Basically boils down to…..

“rules of thumb, educated guesses, or practical shortcuts that guide algorithms toward satisfactory solutions without guaranteeing optimality”

especially those…….

“that enable artificial intelligence systems to solve problems and make decisions efficiently, especially when traditional, exhaustive methods are too slow or computationally infeasible.”

Key Concepts in AI Heuristics

Problem-Solving Efficiency

Guiding Search and Decision-Making

Domain-Specific Knowledge

Rule Implementation and Feature Selection

Trade-Offs (speed, accuracy, and feasibility!)

Typically …………… Search algos and Opt algos…

Spacecraft thermal in general

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Re-entry specific

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Aerodynamics

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Network science in finance and economics

The global financial system can be represented as a large complex network in which banks, hedge funds and other financial institutions are interconnected to each other through visible and invisible financial linkages.

- Breakdown of this link, diversification, propagation of risk. Findings on default cascades to bilateral exposures to overlapping portfolios

Banking:

The dynamic structure of the model is represented as a set of differential equations. This dynamic structure allows us to analyse systemic risk and also to incorporate an analysis of control mechanisms.

Uncertainty is introduced in the system by applying stochastic shocks to the bank deposits, which are assigned as an exogenous signal. The behaviour of the system can be analysed for different initial conditions and parameter sets.

Using core- periphery

Core-periphery structure, the arrangement of a network into a dense core and sparse periphery, is a versatile descriptor of various social, biological, and technological networks.

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Caccioli, Fabio, Paolo Barucca, and Teruyoshi Kobayashi. "Network models of financial systemic risk: a review." *Journal of Computational Social Science* 1.1 (2018): 81-114.

Bazzi, M. Community Structure in Temporal Multilayer Networks, and Its Application to Financial Correlation Networks. University of Oxford, 2016.

Allen, Franklin, and Ana Babus. "Networks in finance." *The network challenge: strategy, profit, and risk in an interlinked world* 367 (2009).

Nagurney, Anna. "Networks in finance." *Handbook on Information Technology in Finance*. Springer, Berlin, Heidelberg, 2008. 383-419.

Money laundering

Savage, David, et al. "Detection of money laundering groups using supervised learning in networks." *arXiv preprint arXiv:1608.00708* (2016).

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Journal

Network theory in Finance

https://www.risk.net/journal-of-network-theory-in-finance

Spam and fake news

Shehnepoor, Saeedreza, et al. "NetSpam: A network-based spam detection framework for reviews in online social media." *IEEE Transactions on Information Forensics and Security* 12.7 (2017): 1585-1595.

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Shu, Kai, H. Russell Bernard, and Huan Liu. "Studying fake news via network analysis: detection and mitigation." *Emerging research challenges and opportunities in computational social network analysis and mining*. Springer, Cham, 2019. 43-65.

More specific, now ML

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Chatzis, S. P., Siakoulis, V., Petropoulos, A., Stavroulakis, E., & Vlachogiannakis, N. (2018). Forecasting stock market crisis events using deep and statistical machine learning techniques. Expert systems with applications, 112, 353-371.

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