

# Large Language Models and Networking: What are the Challenges and Opportunities?

the**Networking**  
Channel



**Anshu Shrivastava**  
Rice U., ThirdAI



**Elisa Bertino**  
Purdue U.



**Jon Crowcroft**  
U. Cambridge  
Turing Institute



**Victor O.K. Li**  
U. Hong Kong



**Ajit Patankar**  
Juniper Networks



Organiser: **Jim Kurose**  
U. Massachusetts

# Large Language Models and Networking: What are the Challenges and Opportunities



Anshumali Shrivastava  
Founder & CEO, ThirdAI Corp.  
Associate Professor, Rice Computer Science.  
[anshu@thirdai.com](mailto:anshu@thirdai.com)

20<sup>th</sup> Sept,

# GenAI/LLMs has our full Attention!

## Generated by ChatGPT

- LLMs and ChatGPT are powerful AI technologies that can help enterprises streamline and automate a wide range of tasks, from customer service and support to content creation and marketing.
- They represent a powerful new tool for enterprises looking to stay ahead of the curve in an increasingly competitive and data-driven business landscape.



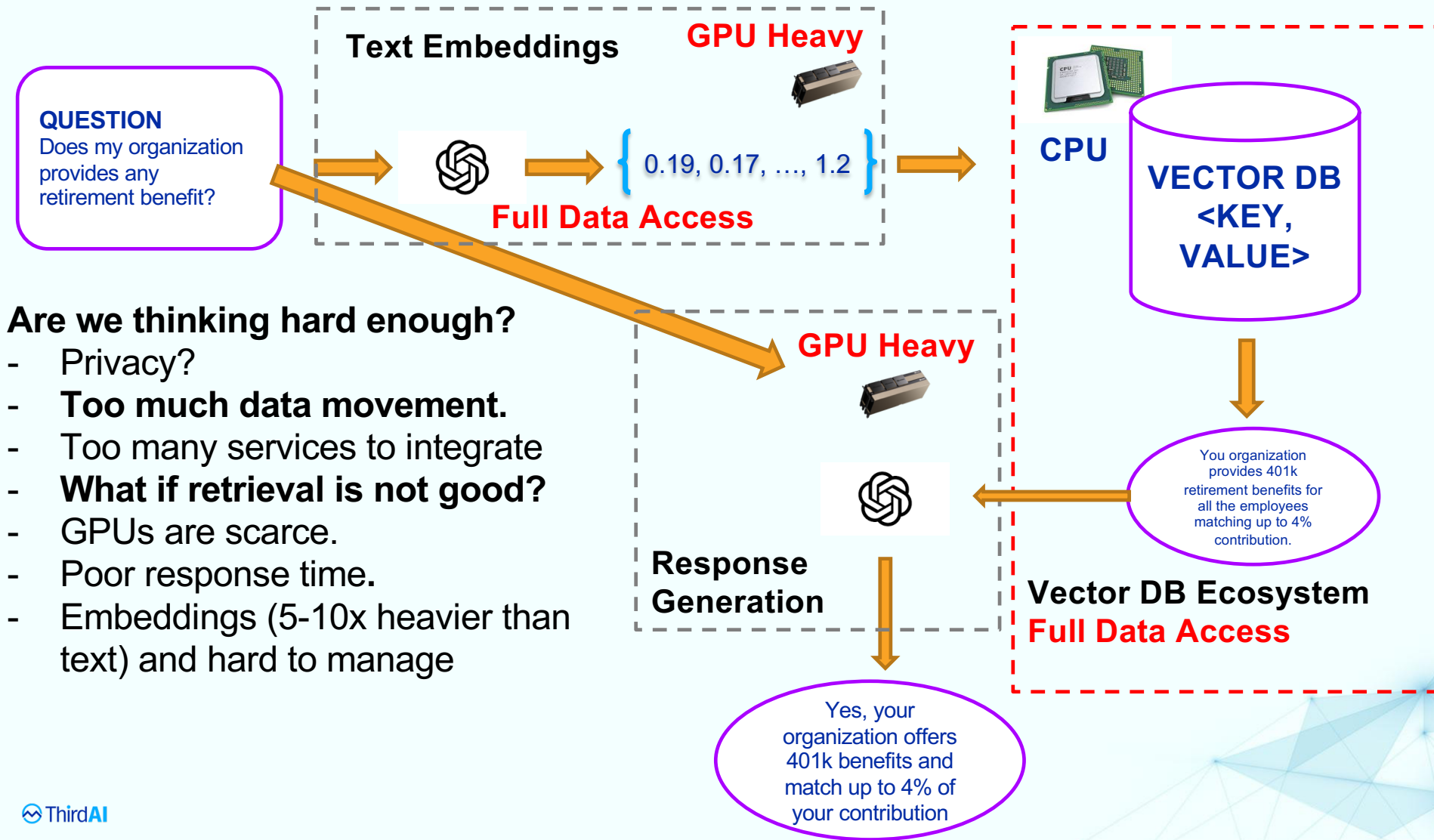
## Early use case for almost all enterprises:

- ChatGPT Assistants on their “domain” text/data with Ownership of the process
- **In Future:** Customized to Fine-grained (or individual) level.

# Many Challenges for Enterprises

- Manage Expectations Well
- Finding the Right Use Cases
- Understanding data privacy and data residency
- Careful with “essentially free” services in production.
- Putting LLM in production is very different and potentially much harder than making a demo.

# Case Study RAG: Why Current Stack is Fundamentally Hard for Production!



## Are we thinking hard enough?

- Privacy?
- **Too much data movement.**
- Too many services to integrate
- **What if retrieval is not good?**
- GPUs are scarce.
- Poor response time.
- Embeddings (5-10x heavier than text) and hard to manage

# Photoelectric Moment in AI: AI is about to be rewritten

1. Our understanding of AI/ML is challenged in a positive way.
2. This is the first iteration of LLMs and it will refine quickly
3. We will surely give LLMs (Mega-AI Models) full chance to solve our hardest problems. After all, what other ideas do we have that we have not tried.



**Efficiency will be the guiding factor!**



slicesRI



PAWR Project Office



acm sigcomm

the**Networking**  
Channel

## Large Language Models and Networking Challenges and Opportunities

*Elisa Bertino*

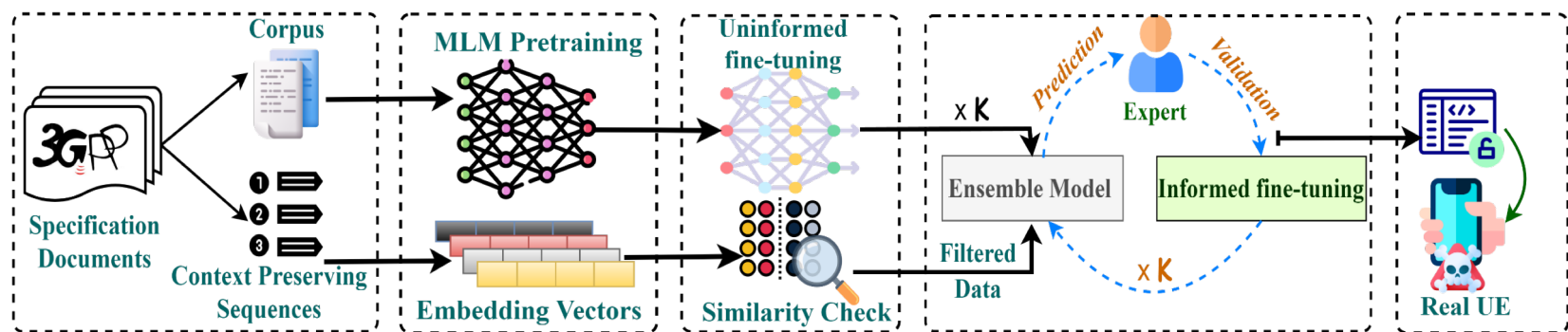
*Purdue U.*

## Opportunity Automatic Vulnerability Detection through Conflicts from NL Cellular Protocol Specifications using LLM

### Challenges

- LLMs are not domain specific
- How do we know where to look for conflicting pairs?
- Formulation: How can LLMs detect inconsistencies?
- No-ground truth for supervised training

### Solution Design



As part of the solution we created SPEC5G a dataset of NL sentences specific to 5G



## Opportunity Automatic Generation of Code

Challenge: correctness of generated code

Initial evaluations [1] on GITHUB COPILOT

- Analysis carried out on code generated by Copilot in scenarios relevant to high-risk cybersecurity weaknesses (e.g. those from MITRE's "Top 25" 2021 CWE list)
- Copilot's performance evaluated on three distinct code generation axes—diversity of weaknesses, diversity of prompts, and diversity of domains
- A total of 1,689 programs were generated
- Of these, 40% were found to be vulnerable

---

[1] H. Pearce et al. "Asleep at the Keyboard? Assessing the Security of GitHub Copilot's Code Contributions" IEEE S&P, 2022

# 2021 CWE Top 25 Most Dangerous Software Weaknesses

Rank	ID	Name	Score	2020 Rank Change
[1]	<a href="#">CWE-787</a>	Out-of-bounds Write	65.93	+1
[2]	<a href="#">CWE-79</a>	Improper Neutralization of Input During Web Page Generation ('Cross-site Scripting')	46.84	-1
[3]	<a href="#">CWE-125</a>	Out-of-bounds Read	24.9	+1
[4]	<a href="#">CWE-20</a>	Improper Input Validation	20.47	-1
[5]	<a href="#">CWE-78</a>	Improper Neutralization of Special Elements used in an OS Command ('OS Command Injection')	19.55	+5
[6]	<a href="#">CWE-89</a>	Improper Neutralization of Special Elements used in an SQL Command ('SQL Injection')	19.54	0
[7]	<a href="#">CWE-416</a>	Use After Free	16.83	+1
[8]	<a href="#">CWE-22</a>	Improper Limitation of a Pathname to a Restricted Directory ('Path Traversal')	14.69	+4
[9]	<a href="#">CWE-352</a>	Cross-Site Request Forgery (CSRF)	14.46	0
[10]	<a href="#">CWE-434</a>	Unrestricted Upload of File with Dangerous Type	8.45	+5
[11]	<a href="#">CWE-306</a>	Missing Authentication for Critical Function	7.93	+13
[12]	<a href="#">CWE-190</a>	Integer Overflow or Wraparound	7.12	-1
[13]	<a href="#">CWE-502</a>	Deserialization of Untrusted Data	6.71	+8
[14]	<a href="#">CWE-287</a>	Improper Authentication	6.58	0
[15]	<a href="#">CWE-476</a>	NULL Pointer Dereference	6.54	-2
[16]	<a href="#">CWE-798</a>	Use of Hard-coded Credentials	6.27	+4
[17]	<a href="#">CWE-119</a>	Improper Restriction of Operations within the Bounds of a Memory Buffer	5.84	-12
[18]	<a href="#">CWE-862</a>	Missing Authorization	5.47	+7
[19]	<a href="#">CWE-276</a>	Incorrect Default Permissions	5.09	+22
[20]	<a href="#">CWE-200</a>	Exposure of Sensitive Information to an Unauthorized Actor	4.74	-13
[21]	<a href="#">CWE-522</a>	Insufficiently Protected Credentials	4.21	-3
[22]	<a href="#">CWE-732</a>	Incorrect Permission Assignment for Critical Resource	4.2	-6
[23]	<a href="#">CWE-611</a>	Improper Restriction of XML External Entity Reference	4.02	-4
[24]	<a href="#">CWE-918</a>	Server-Side Request Forgery (SSRF)	3.78	+3
[25]	<a href="#">CWE-77</a>	Improper Neutralization of Special Elements used in a Command ('Command Injection')	3.58	+6



**HKU-Cambridge**  
**AI to Advance Well-being**  
**& Society (AI-WiSe)**  
**Research Platform**



**HKU-AI WiSe**

# Shaping Large Language Models for Decision-making in Networking

Prof. Victor OK Li  
Director, HKU-AI WiSe



**Faculty of Engineering**  
**THE UNIVERSITY OF HONG KONG**



**香港大學**  
**THE UNIVERSITY OF HONG KONG**

# Outline

- HKU-AI WiSe mission
- Advantages and limitations of Large Language Models (LLMs)
- LLMs can be used to support network decision-making
- Can LLMs answer causal questions to support decision-making?
- Can we make LLMs causal?
- Conclusion

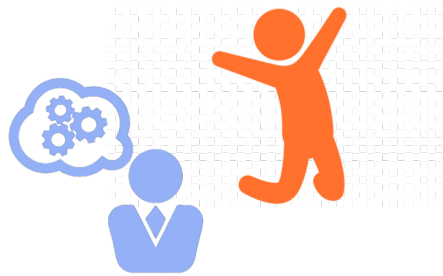
# Our Mission: AI for Social Good



Bring incremental and disruptive changes to the societies, by improving the health and quality-of-life of the people, through the innovation and adoption of AI and big data technologies.



Innovations in  
AI and Big Data  
Technologies



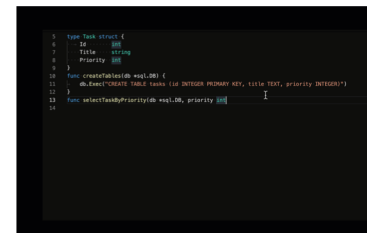
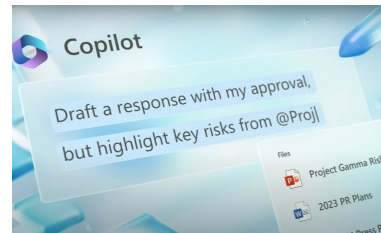
Improving  
Health and  
Quality-of-life



Incremental and  
Disruptive Changes  
to the Societies

# Advantages of LLMs

- Significant increase in performance at large model scale, showing some human-like language abilities [1]
- A key building block in many traditional natural language processing (NLP) tasks, such as machine translation and text summarization [2]
- Integrated into consumer AI to facilitate daily routine tasks
  - Productivity apps
  - Coding/writing assistant
  - ...



[1] Wei, J., Tay, Y., Bommasani, R., Raffel, C., Zoph, B., Borgeaud, S., ... & Fedus, W. (2022). Emergent abilities of large language models. arXiv preprint arXiv:2206.07682.

[2] Min, B., Ross, H., Sulem, E., Veyseh, A. P. B., Nguyen, T. H., Sainz, O., ... & Roth, D. (2021). Recent advances in natural language processing via large pre-trained language models: A survey. arXiv preprint arXiv:2111.01243.

# Limitations of LLMs

- However, they have limitations when used for decision-making
- Social biases and unfairness [1]
  - Trained on data biased towards certain groups of people
  - Results could be discriminatory towards those groups
- Hallucinations [2]
  - Giving answers that sound plausible and confident but are incorrect
  - Tend to generate factual statements that cannot be verified
- Unreliable reasoning capabilities [2]
  - ChatGPT is 63.41% accurate on average in 10 different reasoning categories.
  - Bad at performing complex tasks such as multi-hop reasoning
- Inconsistencies: giving inconsistent answers depending on the phrasing of prompts [3]

[1] Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., ... & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274.

[2] Bang, Y., Cahyawijaya, S., Lee, N., Dai, W., Su, D., Wilie, B., ... & Fung, P. (2023). A multitask, multilingual, multimodal evaluation of ChatGPT on reasoning, hallucination, and interactivity. *arXiv preprint arXiv:2302.04023*.

[3] Krügel, S., Ostermaier, A., & Uhl, M. (2023). ChatGPT's inconsistent moral advice influences users' judgment. *Scientific Reports*, 13(1), 4569.

# Can LLMs Help Network Operation and Decision-making?\*

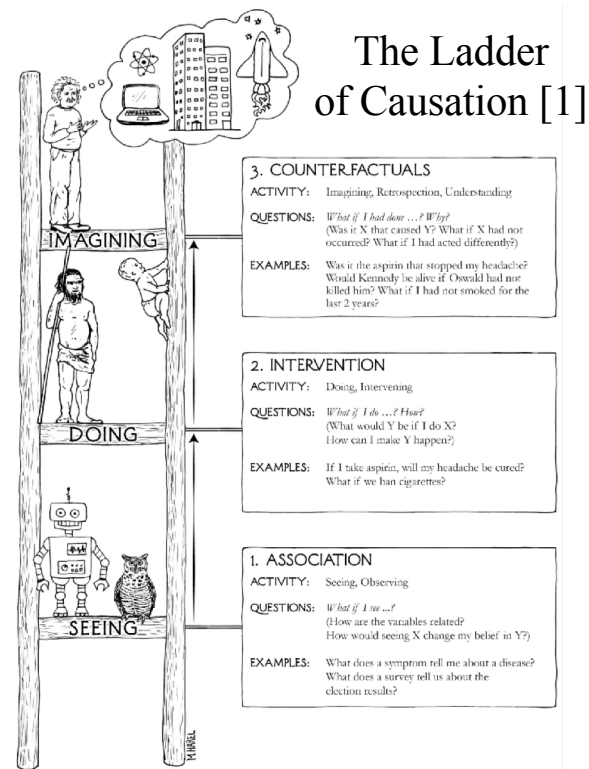
- Predictive Maintenance: LLMs can analyze data from network equipment and predict potential failures.
- Customer Service: LLMs can provide personalized customer support to subscribers.
- Network Optimization: LLMs can analyze network traffic data and identify areas where network capacity may need to be increased.
- Fraud Detection: LLMs can be used to analyze call and data usage patterns and identify potential instances of fraud.

\*From ChatGPT



# Can LLMs Answer Causal Questions?

- Scale is not everything
  - Trained on observational data only
  - Correlation does not imply causation
- It remains challenging for LLMs to
  - Understand causal relationships rather than correlations in data
  - Explain what causes a decision
- Answering causal questions is central in *human* decision-making, making humans unique from robots (see the Ladder of Causation)

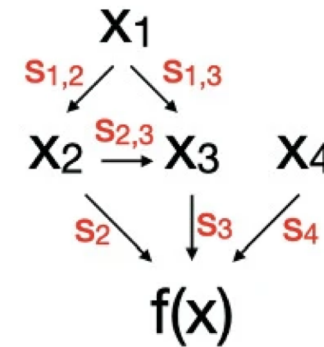


Can LLMs climb to the rung of causal reasoning?

[1] Pearl, J., & Mackenzie, D. (2018). The book of why: the new science of cause and effect. Basic books.

# Causal Models

- Injecting causality into AI models
  - A causal graph:  $X \rightarrow Y$  means  $X$  “causes”  $Y$
  - Causal Shapley values: variable attribution guided by a causal graph [1]
- “What-if” causal explanations [2]
  - Sufficient explanations: an action leading to a particular output, e.g., from  $X = x$  to  $Y = y$
  - Counterfactual explanations: which variables would have had to be different for the outcome to be different?

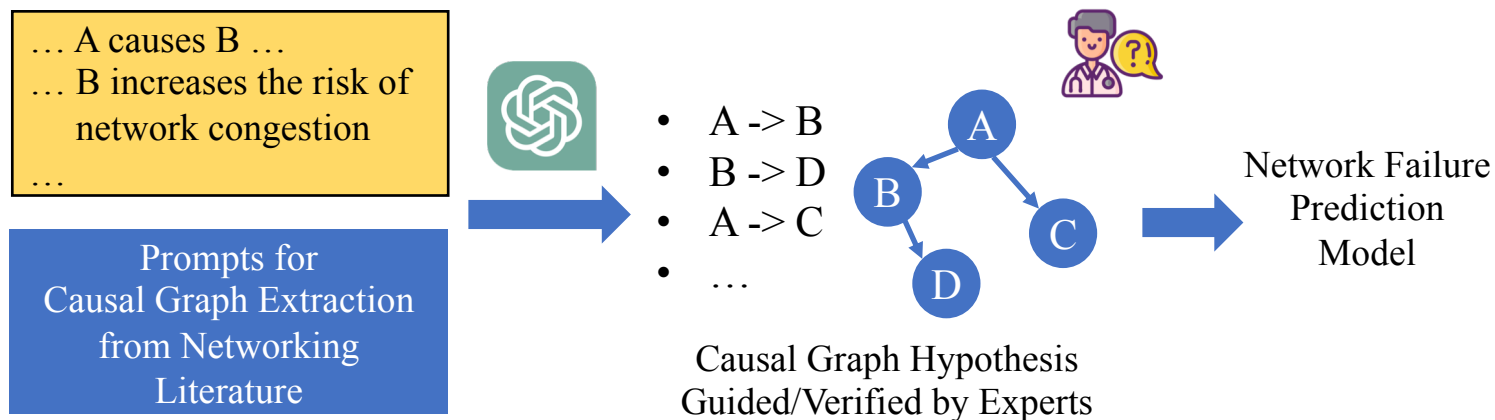


[1] Holzinger, A., Saranti, A., Molnar, C., Biecek, P., & Samek, W. (2022, April). Explainable AI methods-a brief overview. In xxAI-Beyond Explainable AI: International Workshop, Held in Conjunction with ICML 2020, July 18, 2020, Vienna, Austria, Revised and Extended Papers (pp. 13-38).

[2] Beckers, S. (2022, June). Causal explanations and XAI. In Conference on Causal Learning and Reasoning (pp. 90-109). PMLR.

# Can We Make LLMs Causal?

- ChatGPT can be used for text mining of existing networking literature, based on well-designed prompts
- Potential causal relationships between different network entities can be identified
- Such findings can be verified by networking experts



# Conclusion

- AI is a tool to serve humans.
- LLMs have advantages and limitations.
- We need to understand how to best use this tool to our advantage.
- Human beings are unlikely to follow a decision without understanding the rationales.
- Explainability/interpretability is an important step towards trust in AI systems and making AI more useful in decision-making.

# HKU-AI WiSe Team



# Call for Papers

Special Issue of Data and Policy, Cambridge University Press

## **Generative AI for Sound Decision-Making: Challenges and Opportunities**

Guest editors: Victor OK Li, Jacqueline CK Lam, and Jon Crowcroft

**Paper submission deadline: December 5 2023**

Publication: 2024

<https://www.cambridge.org/core/journals/data-and-policy/announcements/call-for-papers/call-for-papers-generative-ai-for-sound-decision-making-challenges-and-opportunities>

# Next event: Lessons learned from 40+ years of the Internet



Organizer: **Henning Schulzrinne**,  
Columbia U, National  
Telecommunications and  
Information Administration

## Highlights from the May 2023 Dagstuhl Seminar

Lessons Learned From 40+ Years of the Internet

( May 01 – May 04, 2023 )

