AMEC Symposium on US Productivity Growth

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Key comments

- Unlikely that GenAI is near maturity; rather, there is a significant amount of co-invention currently taking place, which will likely be disruptive across a number of industries.
- The trajectory is likely different than it has been for predictive ML applications because it produces content, not decisions.
- To see its potential, we should look beyond text “generation” or molecule design. Towards:
  - Summarization and synthesis
  - Agentic models
- There are some threats and unknowns related to timing and impact: workforce, infrastructure, regulation.

1. Synthesize and summarize

- **80%** of corporate data is *unstructured.*
- Emails, Slack channels, performance reviews, HR policies, RFPs, discussion boards, memos, product documentation, customer service logs, …
- We don’t use it well for decision-making.
- But LLMs will help us and it will drive better decisions, product innovation.
- This takes time because it is not “off-the-shelf” but it is already happening in knowledge-intensive organizations.

Example:
Summarizing innovation gaps from patent text documents
(Cheng et al 2024)

Productivity gains from encoding and scaling human expertise

Brynjolfsson, Li, and Raymond 2023

2. Agentic models (Beyond language)

- Allow LLMs to *act*
- Can significantly extend the reach and utility of generative tools
- For example,
  - Acting upon medical records
  - Account management (e.g. changing air tickets)
  - Doing data science
  - Acts like a universal ”API”

Which industries are seeing impact?

- Customer service
- Software engineering
- Product design
- Legal services & consulting?
- Back office productivity?

How likely are LLMs to spur an acceleration of productivity growth over the next decade?

- Gains diffused across sectors in the medium run; suggests fairly constrained job loss

- What about:
  - Data security and privacy?
  - Intellectual property?
  - LLM hallucination?
  - Data prep & engineering?

Tech is rapidly adapting to most industry concerns

	Pros	Cons
Co-Pilots	Ease of use, delivered through existing platforms	Not customized
API calls to foundation models	Leverage huge investments of frontier tech companies	Unknown training data provenance High inference costs Competitive advantage?
Fine-tuning internal models	Firm-specific uses Industry adaptation Addresses some IP concerns Data security	Some engineering required

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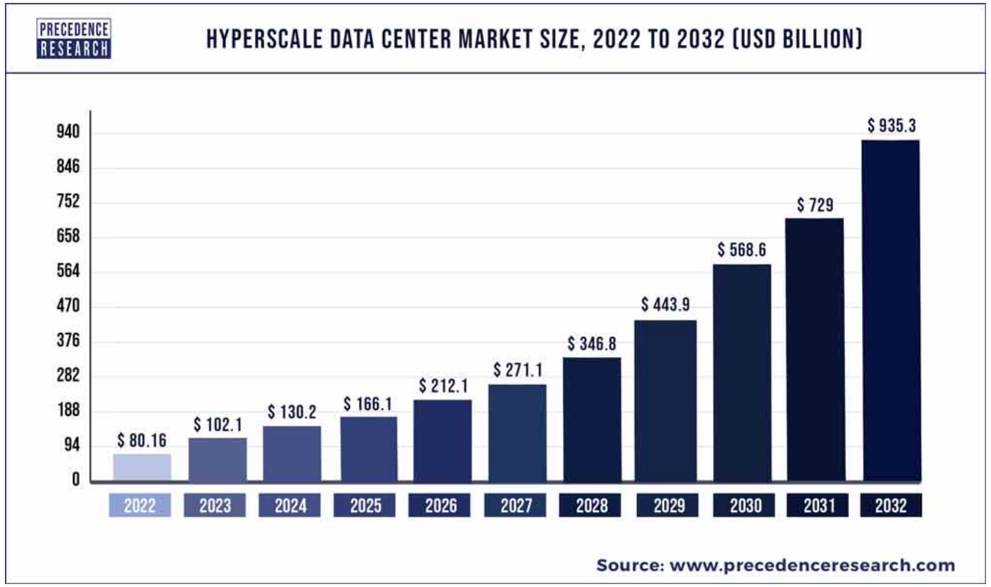
Threats and unknowns: Infrastructure



- How fast will inference costs fall?
- Open questions related to compute and the hardware workforce
- The energy grid, step-down transformers

Threats and unknowns: Regulation

- Data privacy and IP
- Safety in systems
- Ethical frameworks
- Questions around bias are just as pervasive with LLMs and maybe amplified because of the output format
- Scale and competition in the LLM industry

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Threats and unknowns: Workforce

- Workforce transformation
  - Job transformation: integrating co-pilots with work
  - When is output good enough?
  - Dealing with variability in LLM output
  - (Un)explainability of output
  - Intellectual property concerns
  - Output is too convincing, believable
  - Reconstruction of employee training pathways

Measurement remains a challenge

- How do we put this on an empirical footing?
- Capital and software investments are misleading / noisy indicators in the AI economy
- For better attribution, we would like to be able to measure
    - Workforce training investments
    - Infrastructure complements
        - Software development, adaptation
        - Data & data depreciation
        - Computing assets

Measuring AI Inputs: Challenges and Opportunities

http://tambep.github.io/files/AImeasurement.pdf

Thank you.