Adaptive Hybrid Intelligent Systems for the Competitive Advantage of Enterprises

Dietrich Rordorf

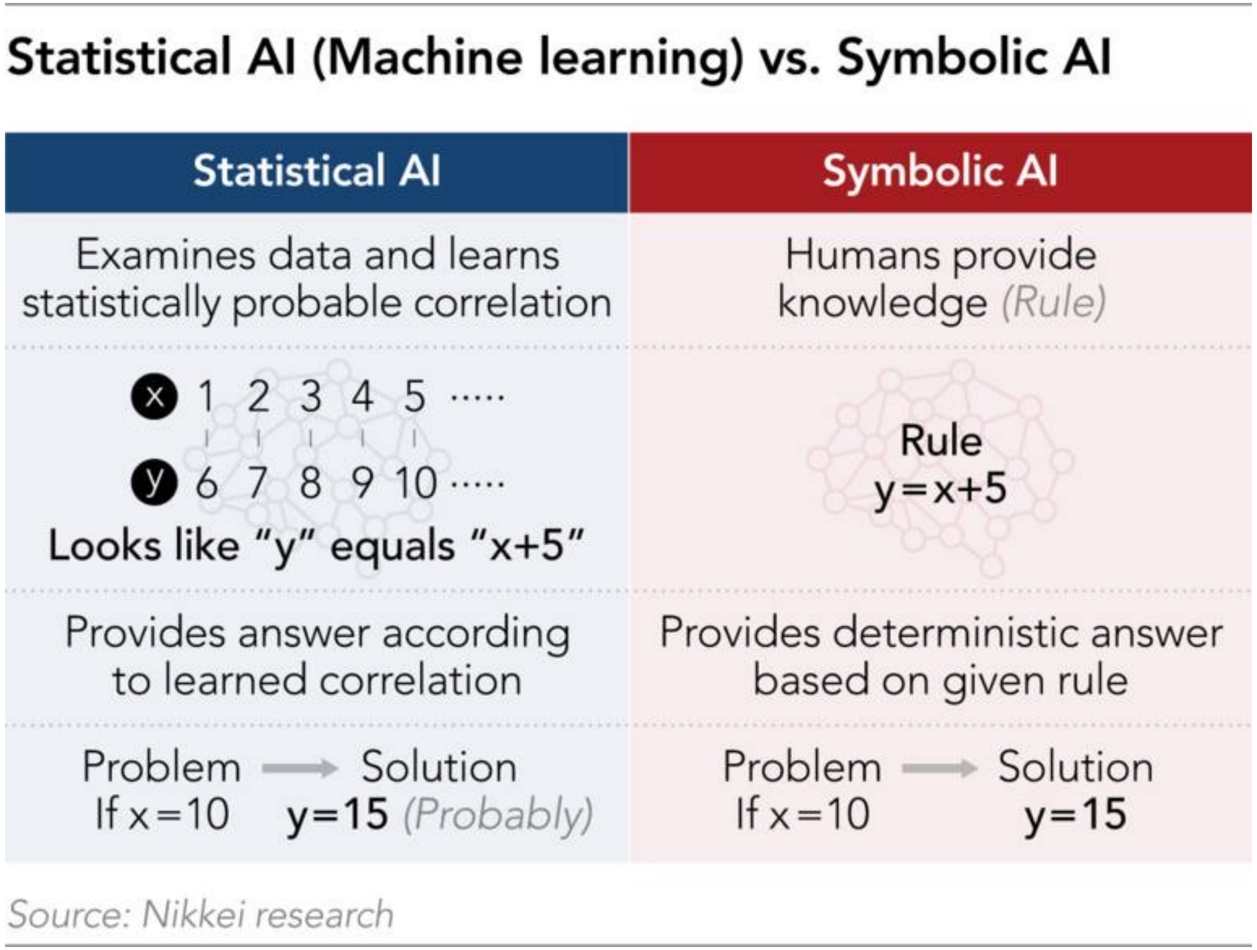
Olten, 19 May 2023

Emerging Topics in Information Systems, SS 2023

Recap

From AI to Hybrid Intelligence

From AI to Hybrid Intelligence



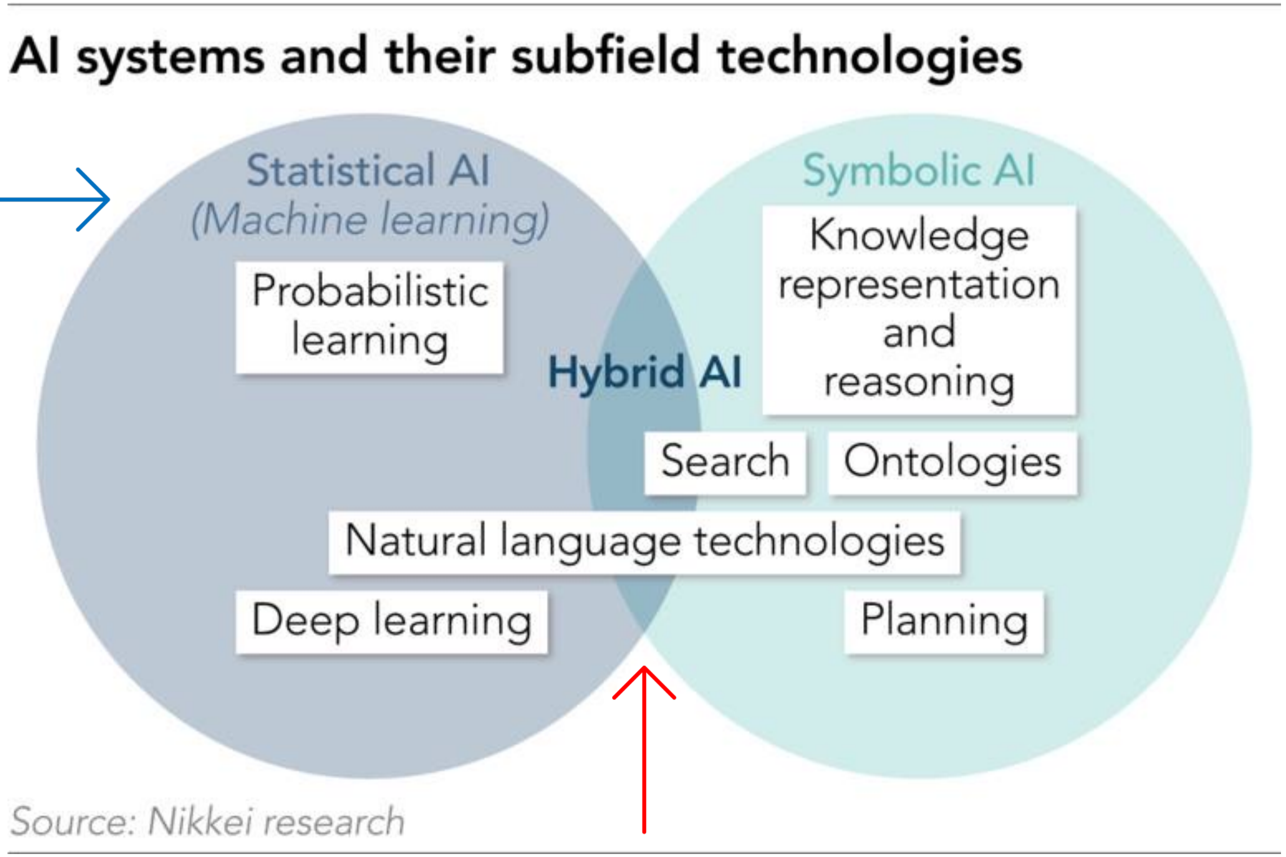
Statistical AI (Machine learning) vs. Symbolic AI

Statistical AI	Symbolic AI
Examines data and learns statistically probable correlation	Humans provide knowledge *(Rule)*
x 1 2 3 4 5 ····· y 6 7 8 9 10 ····· Looks like "y" equals "x+5"	Rule y=x+5
Provides answer according to learned correlation	Provides deterministic answer based on given rule
Problem → Solution If x=10 y=15 *(Probably)*	Problem → Solution If x=10 y=15

Source: Nikkei research

From AI to Hybrid Intelligence

Also: Connectionist
or Sub-symbolic AI



Also: Neuro-symbolic AI, MAKE

From AI to Hybrid Intelligence

- *Hybrid AI* refers to systems combining symbolic and sub-symbolic approaches
- Anywhere from loosely coupled to tightly integrated (d'Avila Garcez & Lamb, 2023)
- Loosely coupled typically involves a human → human-in-the-loop (HITL)
- Tightly integrated: neuro-symbolic AI

From AI to Hybrid Intelligence

- Hybrid intelligent systems: humans and AI work together towards common goals, *augmenting* the human intellect and overcoming human limitations and cognitive biases (Akata et al., 2020).
- Korteling et al. (2021):
    - cognitive abilities of human intelligence are limited by the biological substrate and biological and evolutionary origin of intelligence
    - improve outcomes of AI system by developing human-aware AI systems that support human decision-making rather than pursuing Artificial General Intelligence

Adaptive Hybrid AI

Adaptive AI Systems

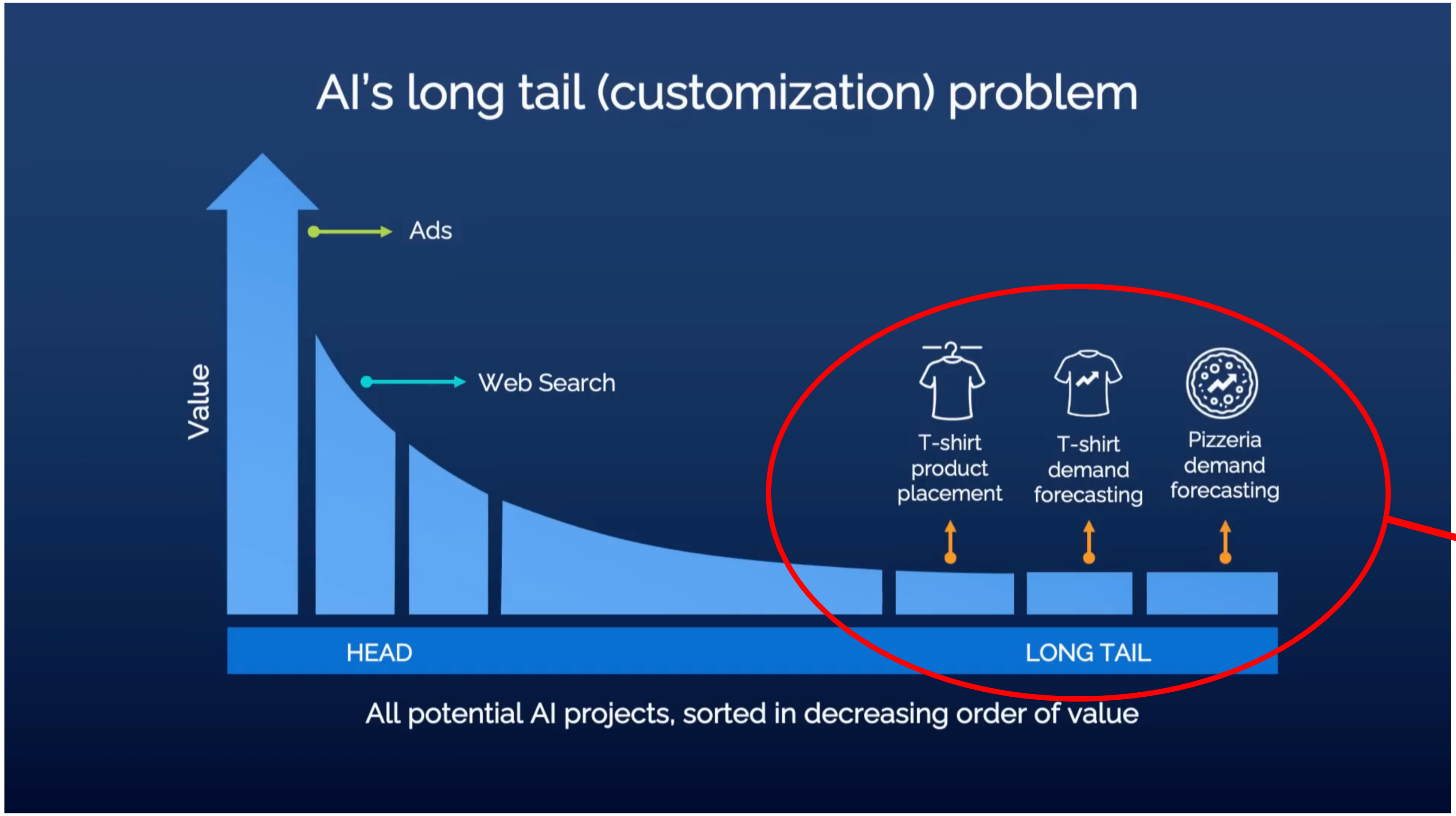
- Human-aware AI systems should **adapt** to (based on non-exhaustive literature review):

  1) Different user's needs
  2) Various user tasks
  3) Joint task completion
  4) Interactions with agents
  5) Changing environment

Adaptive AI – 1) Different User Needs

- Recommender systems, think of Netflix recommendations
- Netflix should learn ***my*** preferences
- **Cold-start problem**: no data about new user
- **Data sparsity problem**: a lot of data in aggregate, but very few data points for each individual user
- Promising hybrid AI approach: graph-learning recommender systems (GLRS) (Zhang et al., 2023)

Adaptive AI – 2) Various User Tasks

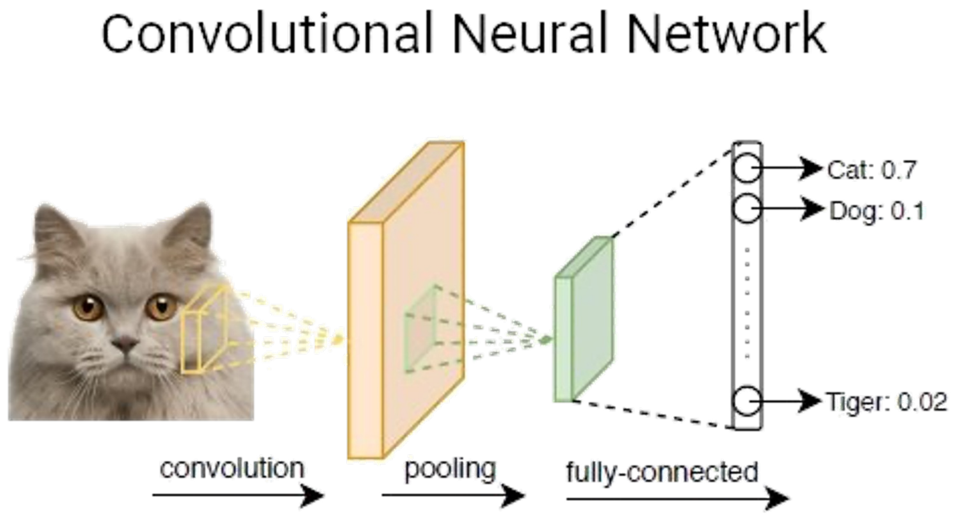


Andrew Ng
TED Talk, 2022
(predates ChatGPT)

Not many working in these areas, but in aggregate represents enormous value.

The Long Tail: Narrow AI?

- “Narrow AI” refers to machine learning models that are trained for one (narrowly defined) use case
- Example:
  - classify animal in image as cat, dog, …, tiger
  - If model has never seen a giraffe in training data, it will classify it as any other animal
- Thus not very adaptable: each use case requires plenty of training examples. Each new class type needs retraining of model.



Narrow vs. Broad AI

ChatGPT

Narrow AI

- Specific use cases, high accuracy
- Requires many specific data examples
- In aggregate very expensive to build as we ned specific data and train a new model for each specific use case
- Does not easily adapt to other tasks (but: transfer learning)
- Does not easily adapt to another user
- If data changes: needs to be retrained

Broad AI

- E.g. LLMs, Foundation Models
- Generic, huge models (dozens to hundreds billions of parameters)
- Emergent capabilities (Wei et al., 2022)
- In-context learning / “few shots learners” (Brown et al., 2020)
- *train-then-fine-tune* or *prompt-based learning*

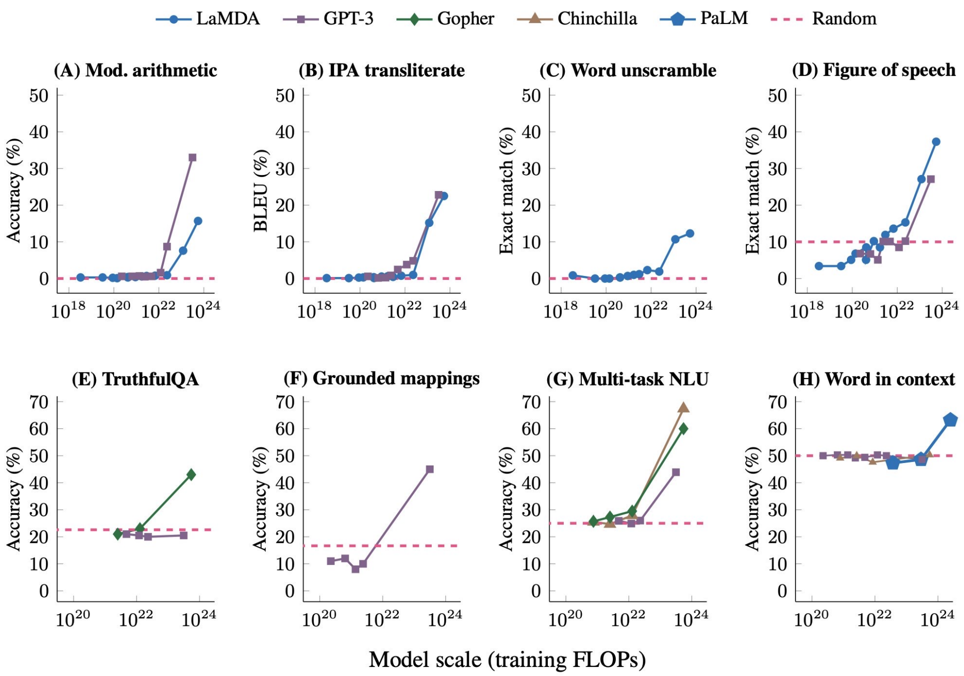
Jason Wei @_jasonwei · Follow

I combed through the large language model literature and made a repository of 137 “emergent abilities”, which are only present in sufficiently-large language models.

100+ emergent tasks can be found in BIG-Bench and MMLU alone.

jasonwei.net/blog/emergence

Scaling seems to work...



Emergent Abilities

Wei et al. (2022)

Performance of models on many NLP and NLU tasks is only ***marginally better than random until a certain model size is reached.***

The Promise of Broad AI

Train-then-fine-tune

- Pre-train large base model (base model for text, base model for image recognition, base model for video sequence analysis, etc.)
- Fine-tune model to specific use cases with few examples only
- Fine-tune model to specific user with few examples only

Prompt-based learning (see, e.g., Zhou et al., 2023)

- user gives an example or two (context)
- AI adapts based on example in context
- (context in GPT3: 2K tokens, ChatGPT: 4K tokens, GPT4: 8k tokens, GPT4-32K: 32K tokens)

Tokens & Context

Given a text string (e.g., "tiktoken is great!") and an encoding (e.g., "cl100k_base"), a tokenizer can split the text string into a list of tokens: ["t", "ik", "token", " is", " great", "!"]

Source: https://github.com/openai/openai-cookbook/blob/main/examples/How_to_count_tokens_with_tiktoken.ipynb

What to put into the context?

- New emerging discipline of "Prompt Engineering"
- Users may need to learn completely new strategies such as *chain of thought* prompting (Wei et al., 2023) and *least-to-most prompting* (Zhou et al., 2023)

Adaptive AI: GitHub Copilot

- Launched October 2021
- AI-powered code completion tool by GitHub & OpenAI
- Trained on public code repos on GitHub.com, GitLab.com, etc.
- Provides suggestions for line completion and entire function blocks
- **Learns and adapts to user's coding style**
- Aims to increase developer productivity
    - Provides boilerplate code, avoids errors (bugs), avoids looking up documentation

Adaptive AI – 3) Joint Task Completion

AI agents need to adapt as part of human-AI teams (Zhao et al., 2022):

- to goals and intentions of the human teammates;
- to cognitive features of the human;
- to physical factors of the human in robot-human interactions (e.g., fatigue of the human); and
- adaptation of learned human models to transfer a learned model to interaction with another human.

Adaptive AI – 4) Others Agents

AI may adapt to other agents:

- changing team composition (new human members, other AI agents)
- AI should account for effects of its own actions on other agents

Multiagent reinforcement learning (MARL):

- AI agent is trained based on the effect of its actions on the environment while consider potential (re)actions of the other agents (Canese et al., 2021).
- MARLtrained AI agent show high adaptability to other agents.

Adaptive AI – 5) Changing Environment

Societal trends, political or legal changes, etc.

- **concept drift**: changes to objectives that AI models were designed for
- **data drift**: changes in the data distribution (Lu et al., 2020)

Requires re-training of AI model to adapt:

- Online training: continuous training and redeploy of AI model
- **Model drift**: performance of continuously retrained model degrades over time

Competitive Advantage of AI

Competitive Advantage of AI

- Davenport (2018):
    - AI primarily used by large enterprises, technology companies, AI start-ups
    - AI capabilities:
        - robotics and robotic process automation (RPA)
        - gaining insights from data through machine learning
        - AI-based engagement with employees, customers through chatbots or intelligent agents
- AI can fuel new business models (Iansiti & Lakhani, 2020)

Competitive Advantage of AI

Types of benefits of AI for enterprises (Ho et al., 2022):

- reduced costs
- improved performance
- better decision-making
- higher customer satisfaction
- better customer segmentation
- improved customer experience
- Better products & services
- business innovation

Hands-on / Discussion

Instructions

- We build 4 groups, ca. 6-7 persons each
- Go to Teams channel for *Emerging Topics > Files > Workshop_Didi*
  - Read the _Group_Assignments.pdf
  - A Powerpoint file is prepared for each group to record your results
  - Each group is confronted with a scenario (see your group’s powerpoint!)
  - Discuss and reason about the adaptive, hybrid AI use case in the group, and to what type of competitive advantage this could lead.
  - Record your results in the powerpoint

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