International Forum on Design Service & Social Innovation
Hong Kong, 27 August 2024

How AI is changing design
New tools, media, and materials

Hugh Dubberly

“Software is eating the world.”

i.e., computers and software are embedded in everything

Q: What do you get when you cross a camera with a computer?
A: a **computer** with a lens

Q: What do you get when you cross a car with a computer?
A: a **computer** on wheels

Q: What do you get when you cross a bookstore with a computer?
A: a **computer** software services company, e.g., Amazon

“My own theory is that
we are in the middle of a dramatic
and broad technological and economic shift
in which software companies
are poised to take over
large swathes of the economy.”

— Marc Andreessen, “Why Software Is Eating the World,” WSJ, 2011
https://a16z.com/why-software-is-eating-the-world/

Software is also eating design.

- In **graphic design,** printing is disappearing
- In **industrial design,** mechanical devices are disappearing
- In **interaction design,** mobile apps have peaked
- In **service design,** soon every activity will be augmented with data

...and creating new forms of design.

What is the new design?

The emerging era of design has no agreed-on name, yet.

Richard Buchanan has proposed **“Fourth-order Design.”**

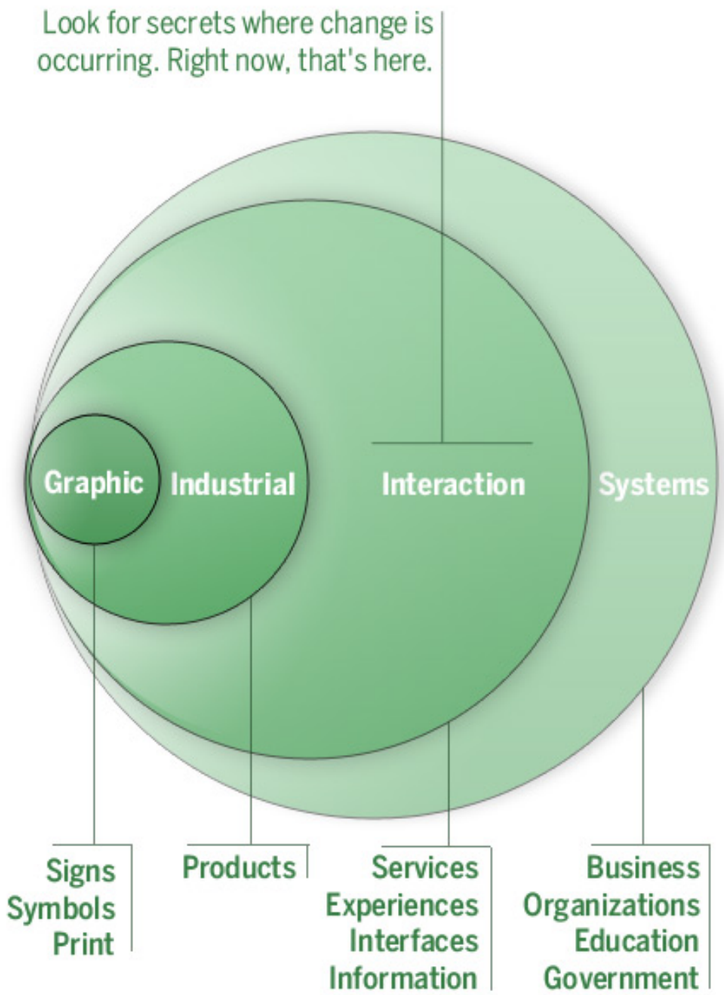
Terry Irwin has proposed **“Transition Design.”**

Jodi Forlizzi had described designing for **“Product-Service Ecologies.”**

John Maeda has proposed **“Computational Design.”**

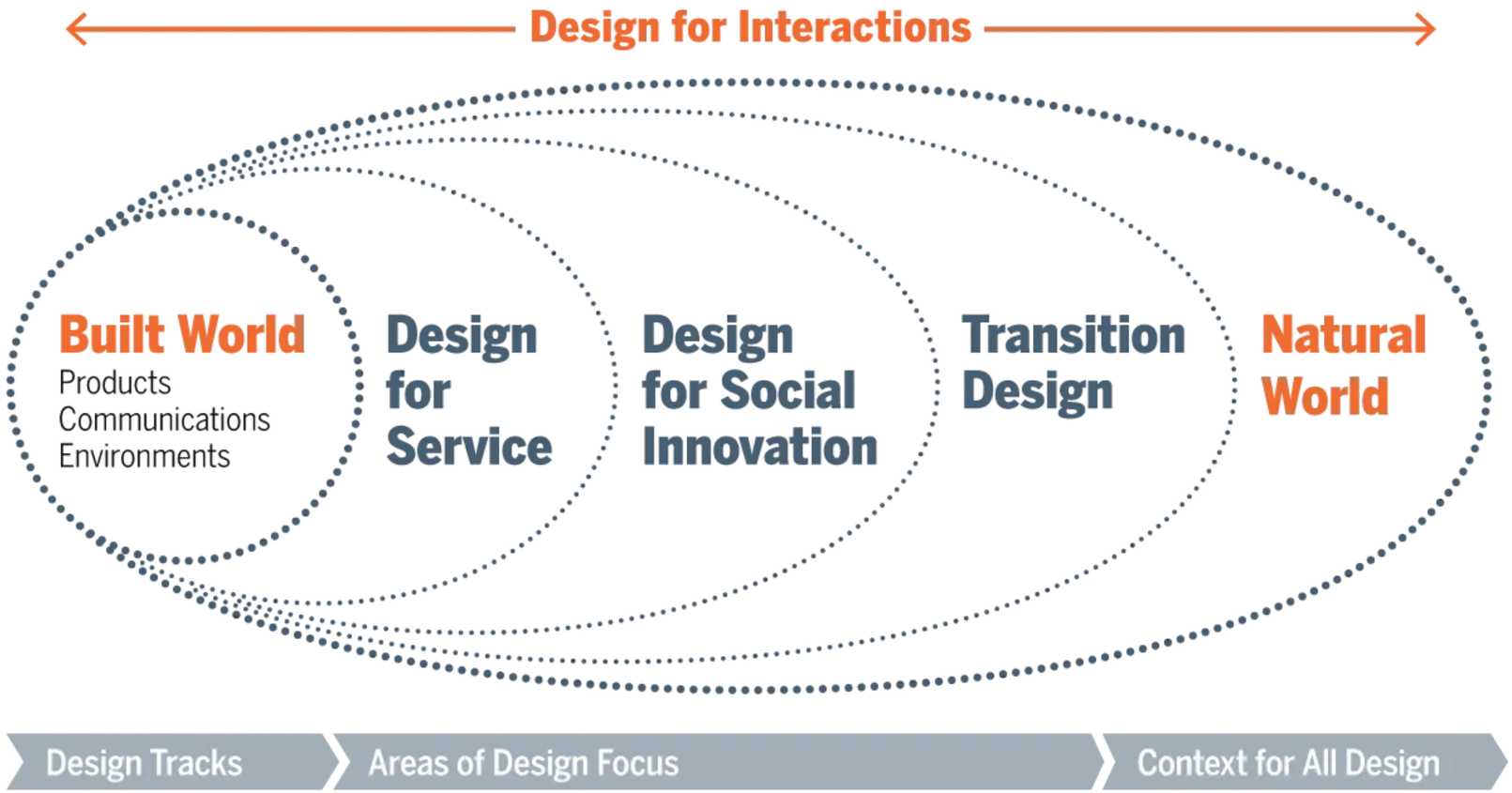
John Cain has proposed **“Data-enabled Design.”**

“Fourth-order Design” focuses on “environments and systems.”



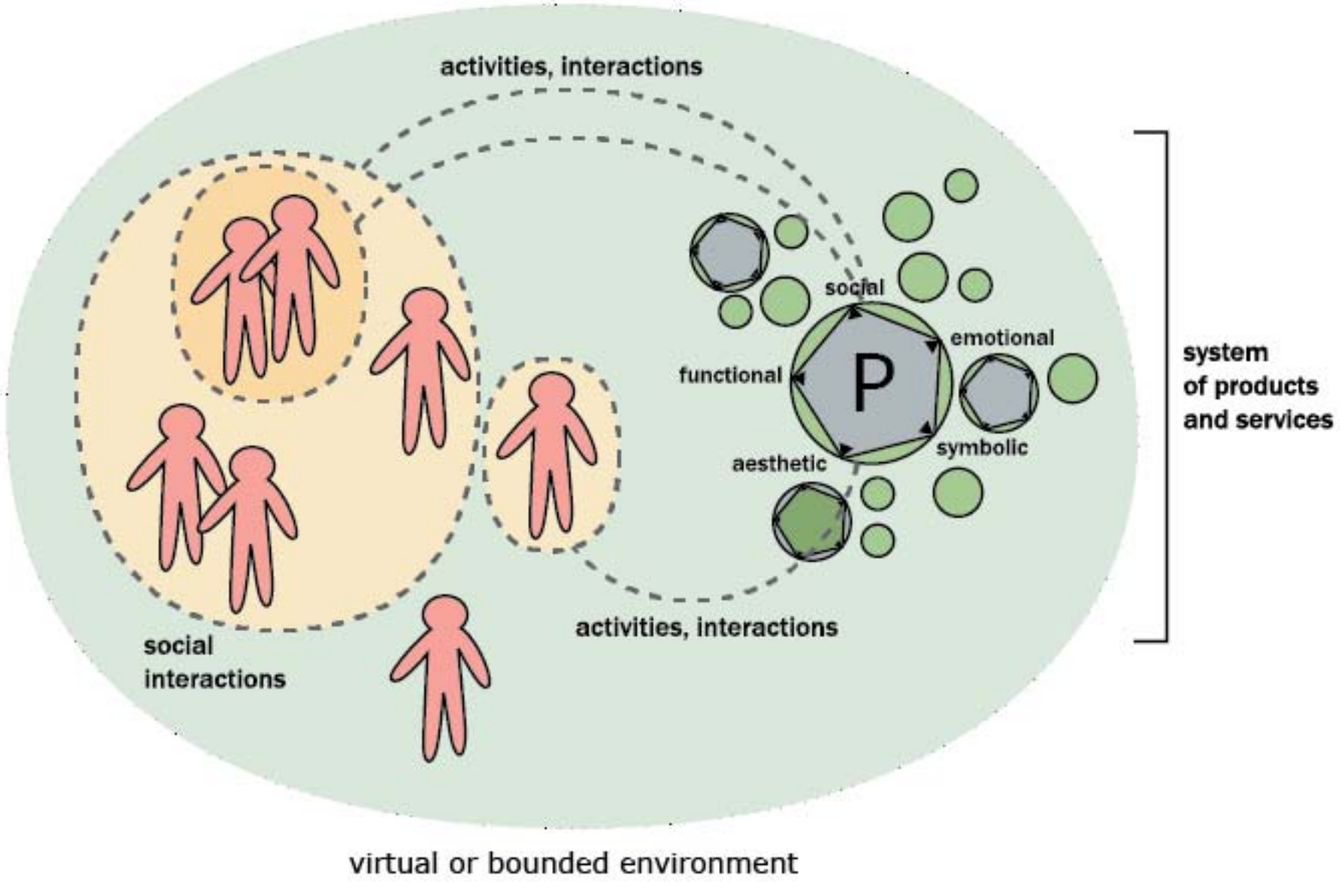
Cf. “Wicked Problems in Design Thinking,” Richard Buchanan, 1992.

“Transition Design” focuses on “systems-level change to create more sustainable futures.”



Cf. Terry Irwin, Gideon Kossoff, and Cameron Tonkinwise, 2015.

“Product-service ecologies” are systems of systems, integrating hardware, software, and human organizations.



Cf. “The Product Service Ecology: Using a Systems Approach in Design,” Jodi Forlizzi, 2013.

“Computational Design” focuses on “keeping pace with current paradigms in technology.”

Cf. “Design In Tech Report 2018,” John Maeda

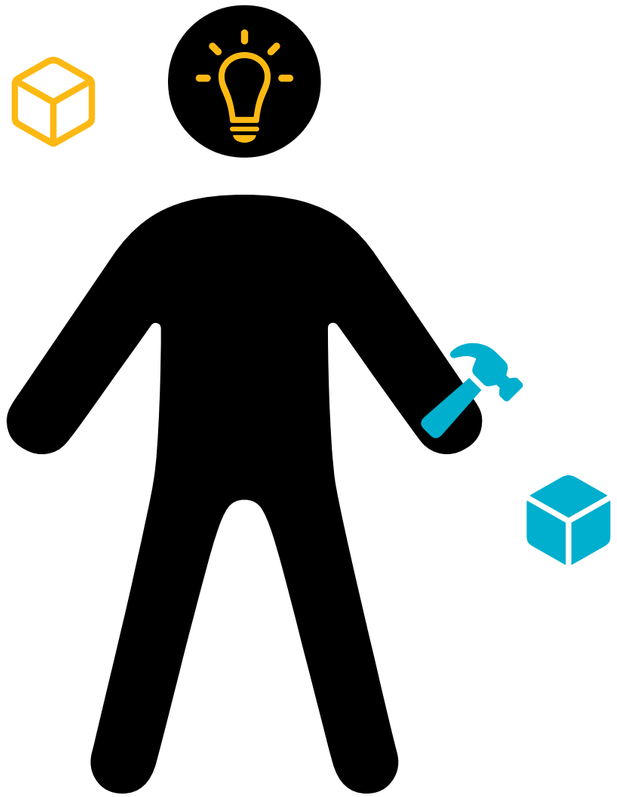
“Data-enabled Design” forefronts data as a material of design.
Consider these four eras.

- 1900: **Design for Manufacturing**
  graphic design + industrial design emerged
- 1985: **Computer-aided Design for Manufacturing**
  personal-computer-based tools became standard
- 1995: **Design for Experience**
  interaction design + service design emerged
- 2020: **Data- [and AI-]enabled Design for Experience**
  data- [and AI-]based tools will become standard

Cf. “Navigating Design, Data, and Decision in an Age of Uncertainty,” by John Cain and Zach Pino
https://www.sciencedirect.com/science/article/pii/S2405872623000448

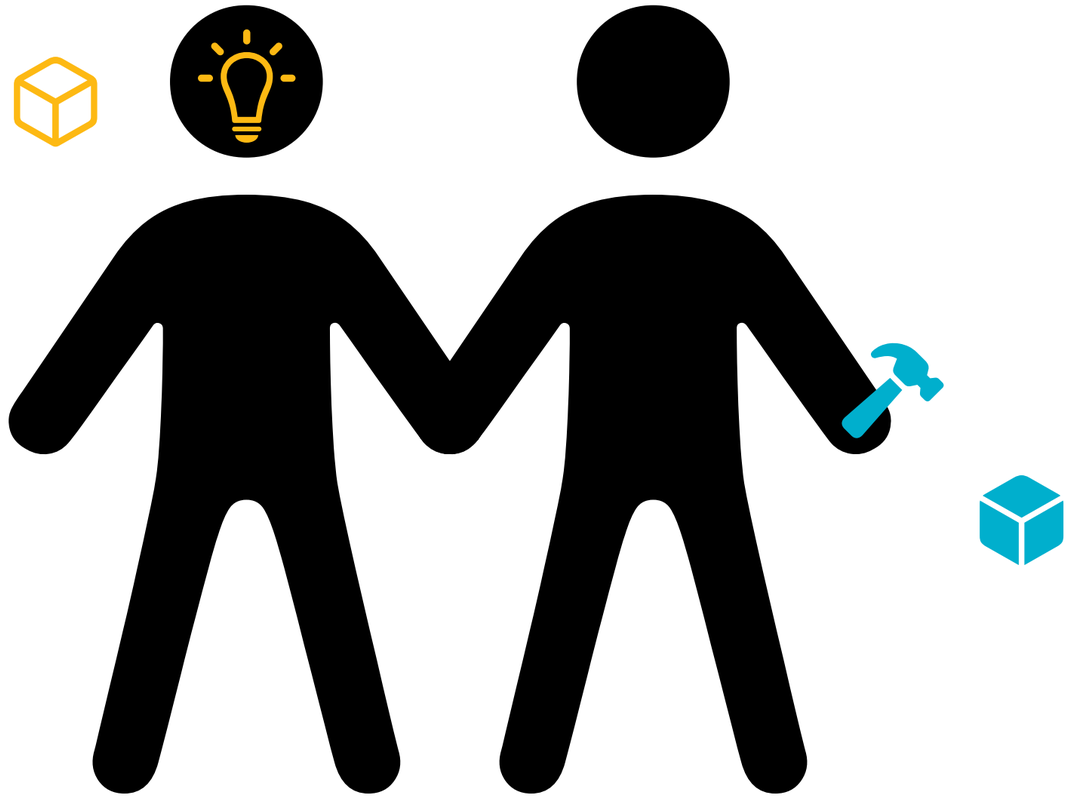
Where did this start?

Around 1900, mass production emerged — **and “planning” and “making” became separate jobs.**



One role: **planning-while-making**

became



two roles: a **planner** of the artifact (and process) and **maker** of the artifact.

Huge technological changes created the need and space for design —

- **artificial materials** augmented natural stone, clay, wood, and plant fiber:
  e.g., paper, steel, plate glass, reinforced concrete, aluminum, plastics

- **artificial sources of energy** augmented human and animal muscles:
  e.g., falling water, steam expansion, internal combustion, nuclear fission

About 1965, professional design began a **transition to computers.**

- First, as **tools** for creating specifications (for manufacturing)
  e.g., Autocad, Illustrator, Photoshop, InDesign, Rhino, Figma

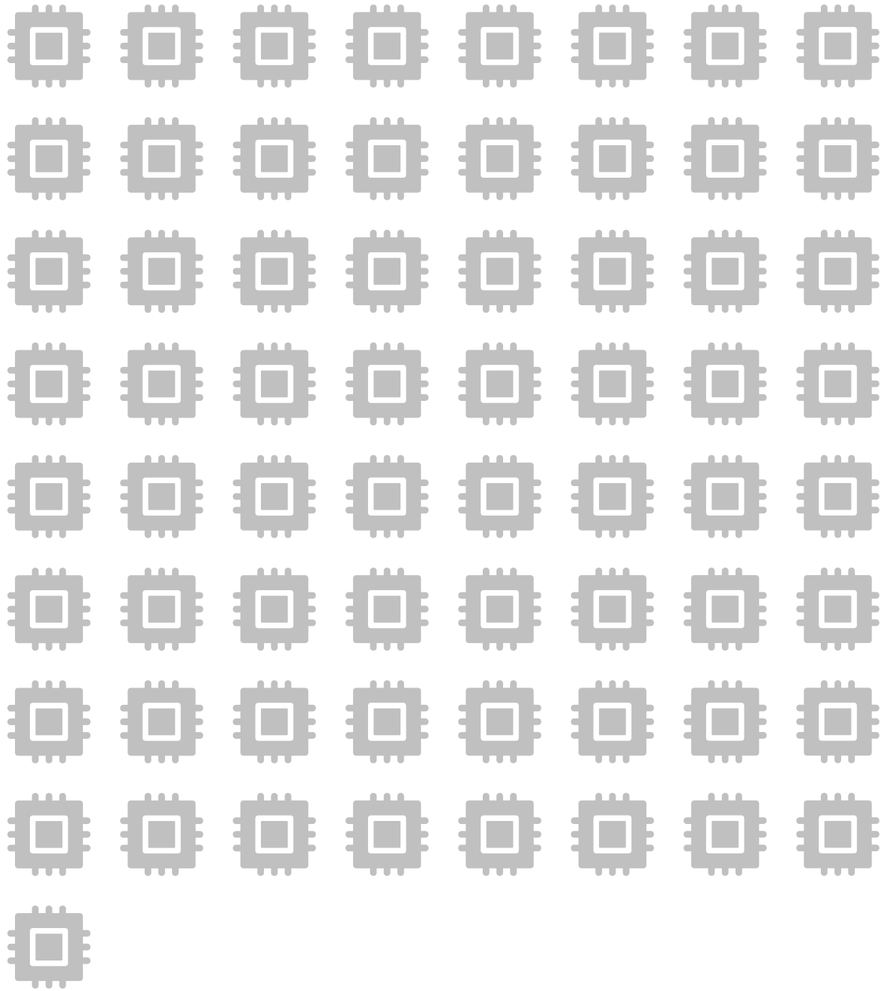
- Then, as **media** for publishing and collaborating
  e.g., Email, FTP, the world-wide web, Processing, Mural, Zoom

- And more recently, as **materials** with which we design
  e.g., PC apps, web sites, web apps, mobile apps, device UIs

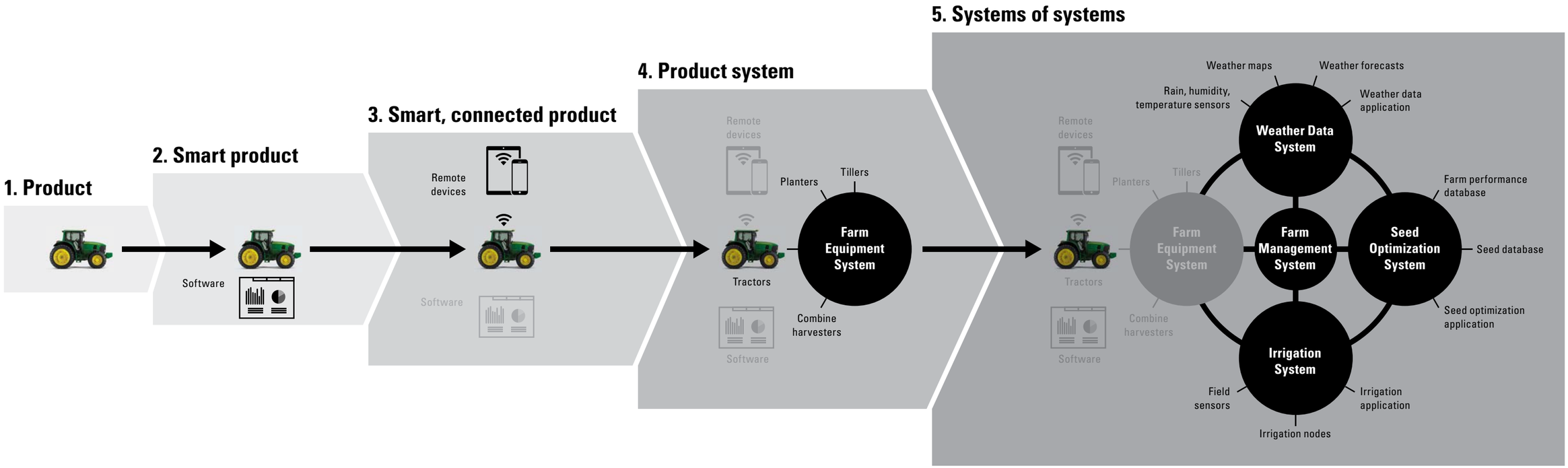
How has technology changed?

Computers used to be scarce; now **micro-processors are in everything.**

A Tesla includes about 65 “computers.”



Products used to “stand alone”; now they are **“smart and connected.”**



Cf. “How Smart, Connected Products Are Transforming Competition,” by Michael Porter, HBR, 2014

Sensors are on chips, “printed” in the billions.

The iPhone 15 includes more than a dozen sensors.

3 cameras in the back:
Ultra-wide
Telephoto
Wide

LiDAR scanner

Radios:
Bluetooth
Cellular (5G + LTE ×4)
GPS + GLONASS
iBeacon microlocation
NFC
Ultra Wideband
Wi-Fi (×2)

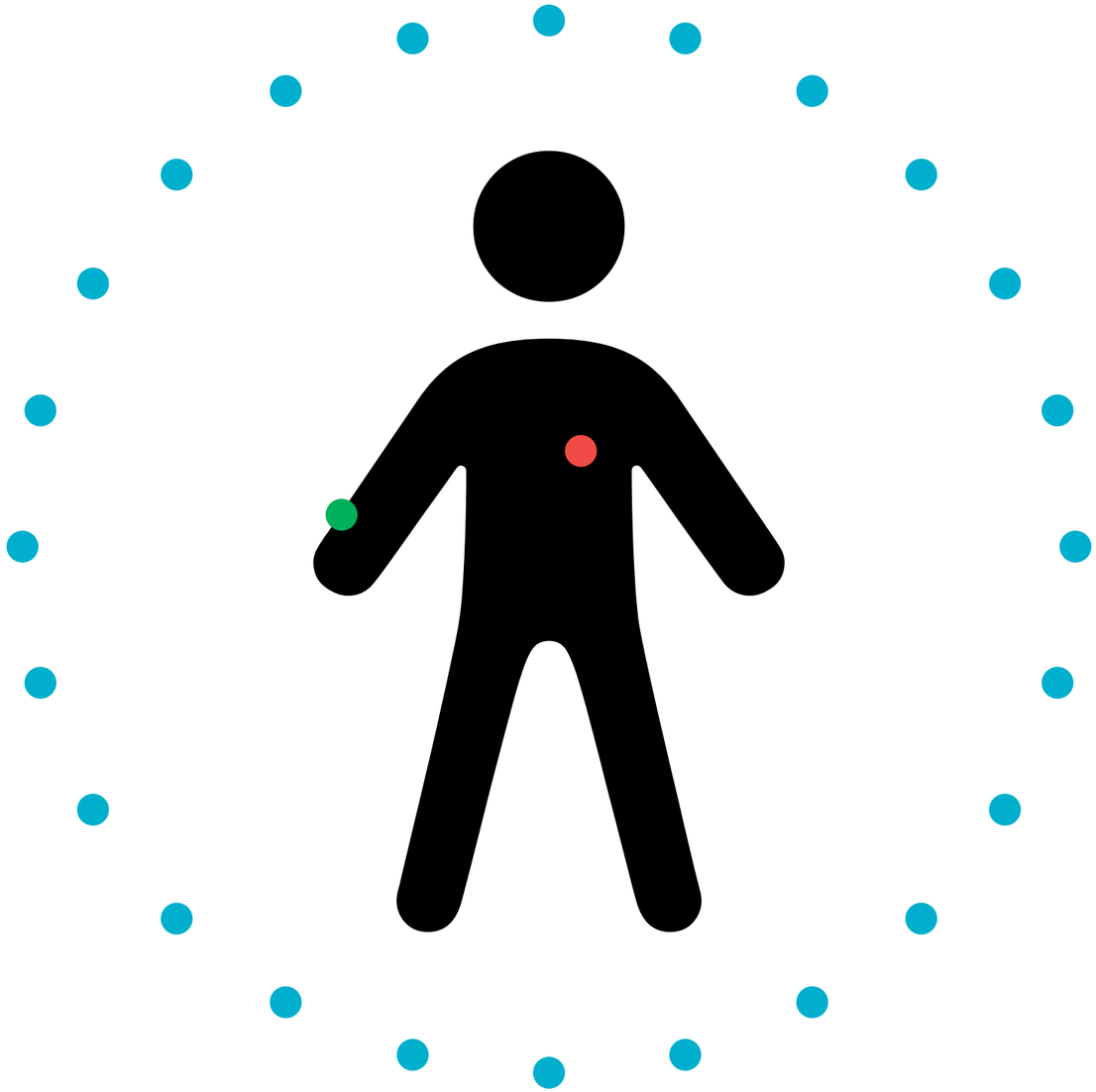
1 camera in the front
Microphone
Dual ambient light sensors
Proximity sensor (infrared)
2 infrared cameras (for FaceID)

Touch screen with ‘Haptic Touch’

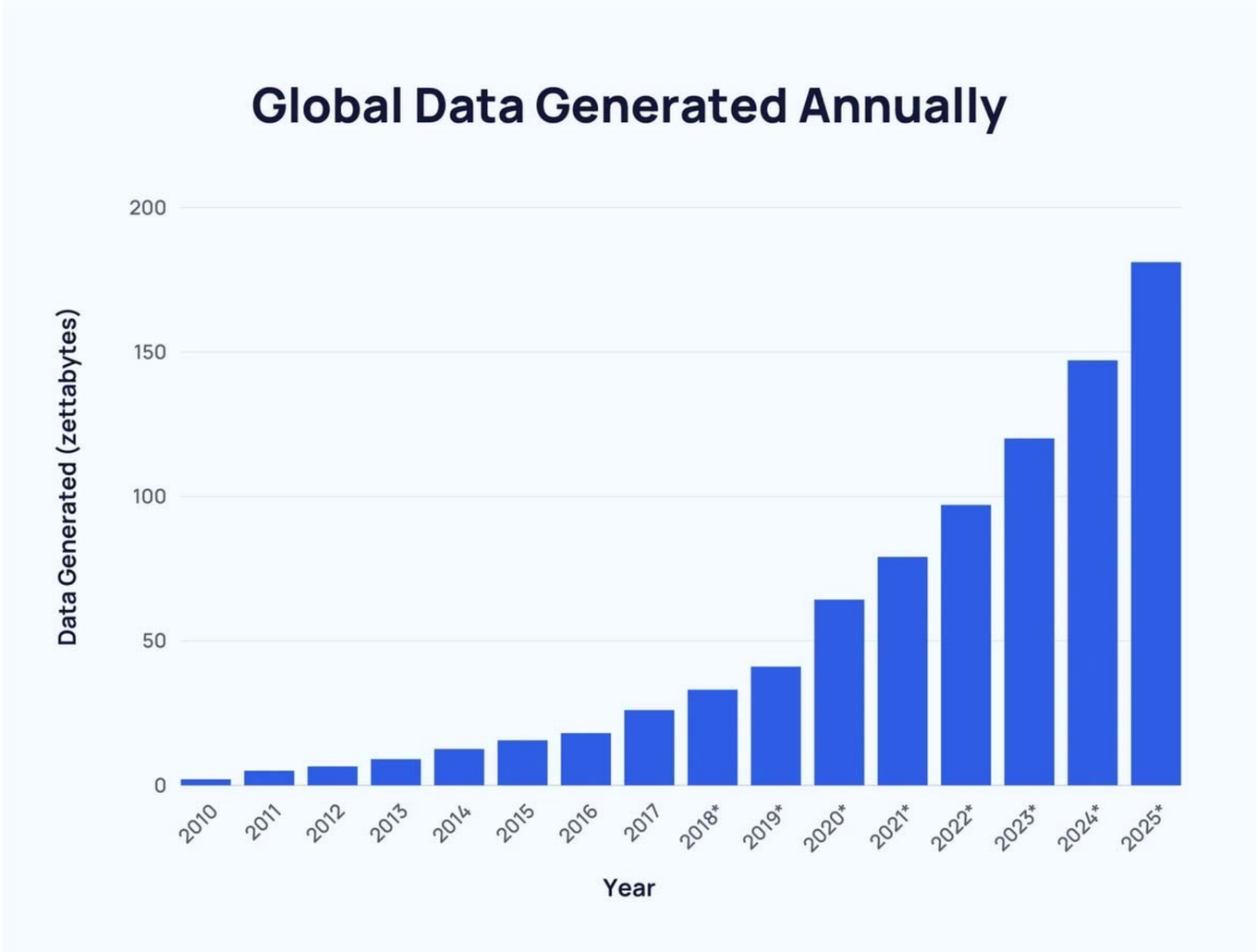
2 internal moisture sensors
Barometer (for altitude)
Accelerometer (3-axis)
Gyroscope (3-axis)
Magnetometer (compass)

Dual microphones

And sensors will be all around us, on us, and in us — measuring **everything, everywhere, all the time.**



Large populations and lots of sensors are creating **oceans of data.**



https://explodingtopics.com/blog/data-generated-per-day

Sensors and smart-connected products are creating a **new era of data.**

1. Era of data scarcity— origins of data science, early 19th century	**2. Era of small data sets**— classical statistics developed, late 19th century	**3. Era of mass-produced data**— late 20th century, “macroscopes” emerge	**4. Era of measuring everything**— early 21st century, “macroscopes” become ubiquitous
Data sets were few + infrequent (e.g., census)	Individual scientists working independently	Teams of scientists using computer-controlled instruments	A few large organizations assemble immense data sets (e.g., Google, NSA)
Based on manual sampling	Collect few samples and make many measurements (noise becomes a problem)	Automatic sampling, producing digital data	Millions of measurements of millions of things (much data goes unused)
Producing analog data	Questions remain simple but important (e.g., Which treatment is better?)	Multivariate analysis becomes important	Computing power and band-width gate analysis
Applied to simple but important questions	Correlating an effect with change in a single variable becomes standard of proof	Number and complexity of questions increases	Machine learning comes into its own (overfit becomes a risk)

Based on a model by Jeff Leek and Brad Efron.

Data are defined by 5 dimensions

or maybe 10

1 **Volume:** the amount of data,
posing challenges for storage, processing, and analysis

Validity

2 **Velocity:** the speed of data production and processing,
from large intervals to near real-time streams

Variability

3 **Variety:** the types of data available,
from unstructured to semi-structured to structured

Volatility

4 **Veracity:** the quality, reliability, and accuracy of data,
also the actionability

Vulnerability

5 **Value:** the results of decisions data enables,
moving from measurement to effective action

Visualization

https://datasciencedojo.com/blog/10-vs-of-big-data/

Data structures decompose into 5 basic forms — “primitives”:

Primitive 1

Point

e.g, name-value pairs, nodes + links

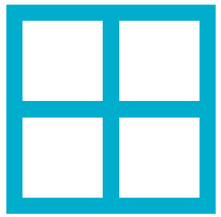
Primitive 2

Line

e.g., array, string, list, timeline

Primitive 3

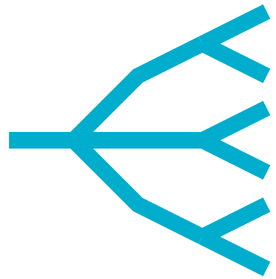
Matrix



e.g., table, spreadsheet, bitmap image

Primitive 4

Tree



e.g., outline, hierarchy, taxonomy, venn diagram

Primitive 5

Web

e.g., graph, network, ontology

Data arise from processes, whose participants (e.g., designers)...

- **frame** questions (with regard to values + context)
- **select** variables to measure (within constraints)
- **deploy** instruments (that have range, resolution, frequency) (subjected to noise, entropy, and confusion)
- **wrangle,** render, and present their measurements
- **interpret** what their measurements “mean”
- **decide** how to respond and act

The word “data” may sound objective, even scientific.

What organization doesn’t want to be “data-driven”?
But data always “argue” for something.
Like other artifacts and like design, **data are inherently political.**

Where’s this going?

Data “enables” social-technical systems in fundamental ways:
communication, control, interaction, conversation, and learning

- Data enables **feedforward**
    - measure, signal, act
    - identify, sort, match
- Data enables **feedback** — compare current and preferred
    - negative (stabilize): detect error and act to reduce it
    - positive (grow): detect success and act to increase it
- Data enables **modeling**
    - predict behavior and outcomes
    - simulate systems

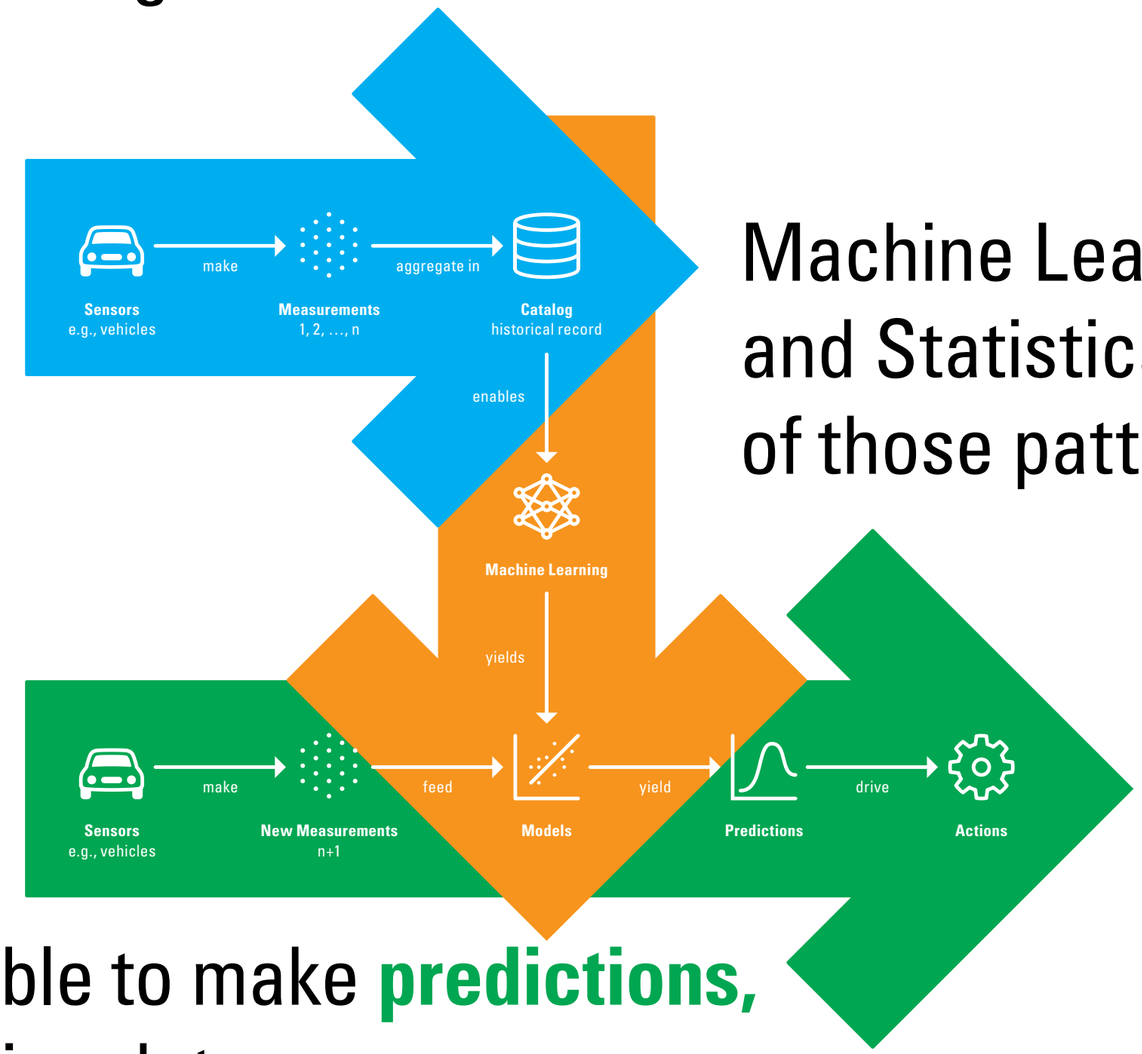
Data “enables” design in several ways:

- **Personalize** communications and experiences to fit individuals:
  One size doesn’t have to fit all; treat everyone as unique.
  Continuously adapt to each person’s goals, history, and context.

- **Improve** products and services based on metrics:
  Instead of guessing, measure what people want and do —
  not just small, infrequent samples but the whole, all the time.
  Continuously A/B test options to continuously improve.
  Monitor every process; build feedback into every system.
  Build in the data collection needed for the next version.

- **Learn** from history:
  Collect, wrangle, and normalize data; build large reservoirs.
  Process and correlate the data to find insights and patterns.
  Create pipelines for sharing and refineries for processing.

Even small **"data lakes"** contain patterns — correlations and repeating behaviors.



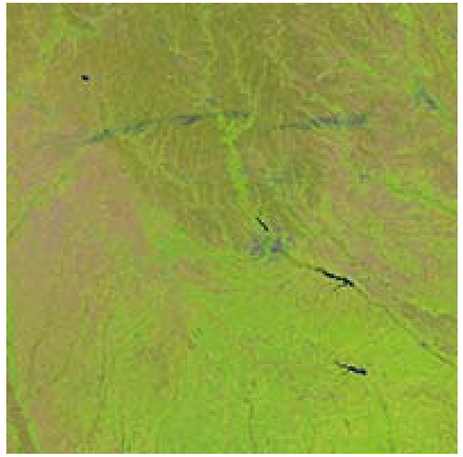
Machine Learning (ML) and Statistics yield **models** of those patterns.

Models make it possible to make **predictions,** based on new, incoming data.

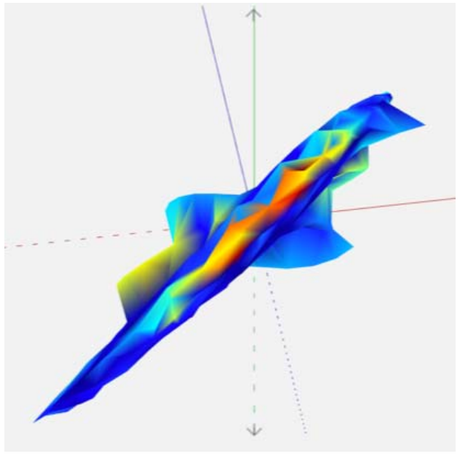
Such predictive models are at the heart of modern AI.

For example, they can predict

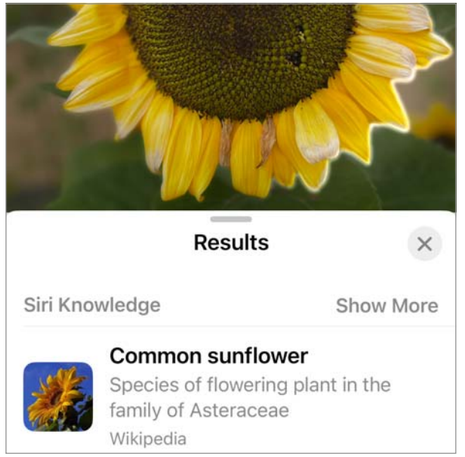
what the weather will be
in ten days,
based on data from today



total corn crop yield
for the world,
based on satellite
and weather data



if a patient has
a heart blockage,
based on a 3D cardiogram



who or what
a photo depicts
(image recognition)

"And it came to pass that a man was troubled by a peanut butter sandwich, for it had been placed within his VCR, and he knew not how to remove it."

what the next word
in a sentence should be
(Generative AI)

Target predicted a teenager was pregnant based on publicly-available data, before her parents knew!

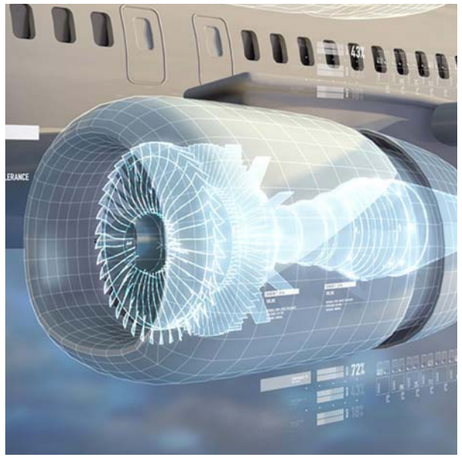
Target found that families change their shopping habits when they have children which, in 2012, led them to develop a pregnancy prediction algorithm—a digital twin of customers, drawing from many sources:

- credit card companies
- credit bureaus
- search engines
- magazine subscriptions
- job history (e.g., LinkedIn)
- public records on marriage, birth, divorce, and bankruptcy
- social media posts
- and especially what you buy—your purchase preferences.

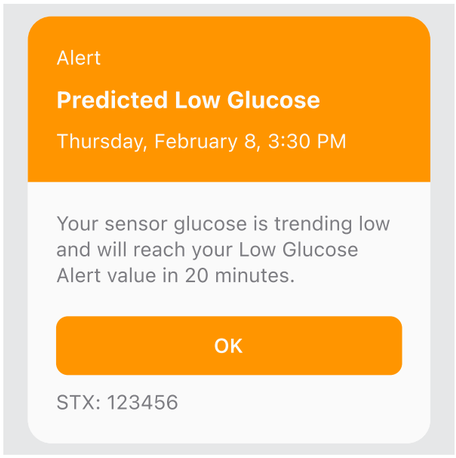
https://www.nytimes.com/2012/02/19/magazine/shopping-habits.html

Predictive models are also at the heart of digital twins — algorithms that simulate the operation of artificial and natural systems.

For example:



Predicting when
a jet engine will fail
based on vibration data.



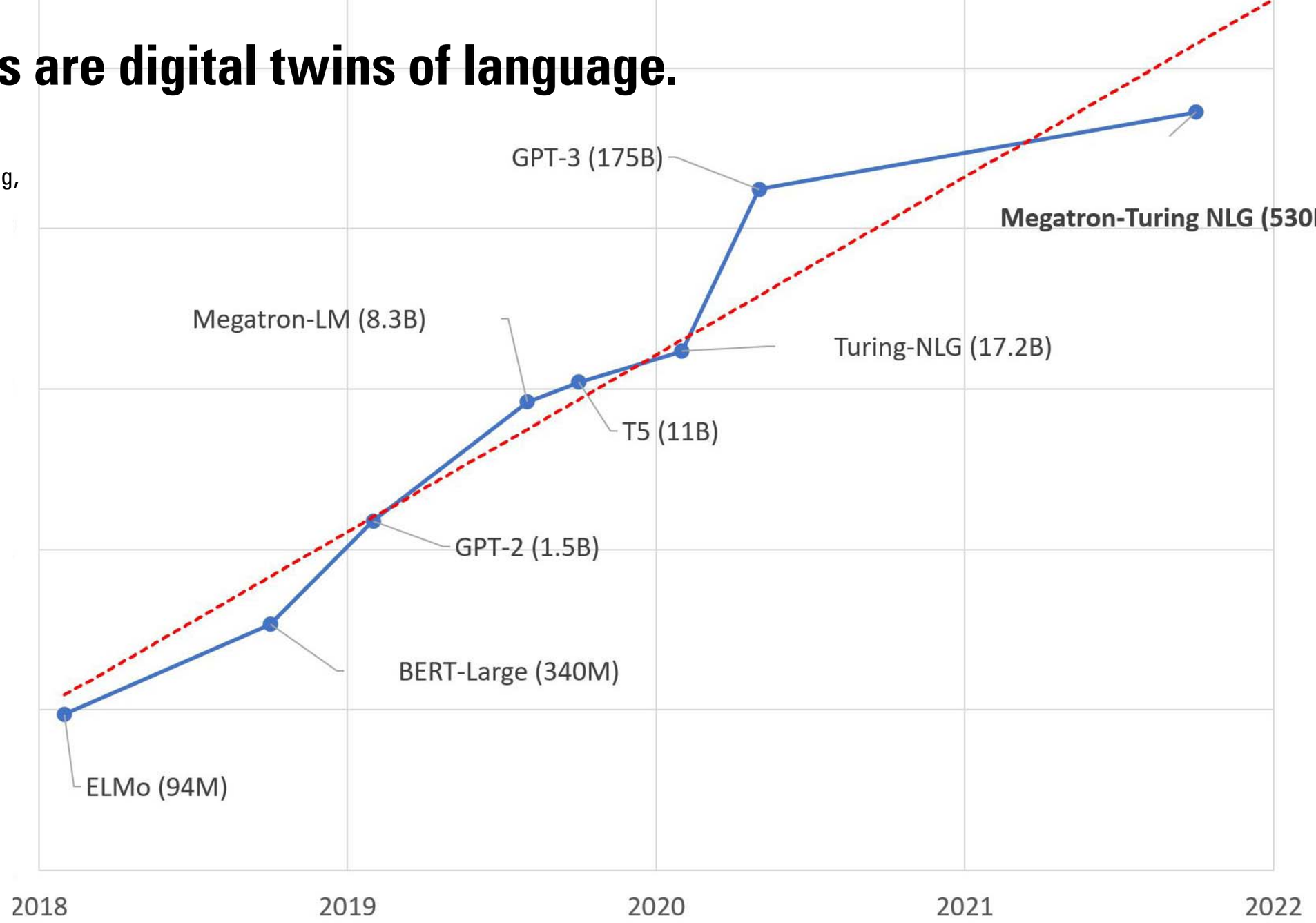
Predicting when
a person's blood sugar level
will crash
based on exercise,
food, and insulin.

In a sense, LLMs are digital twins of language.

The latest wave of machine learning,
Generative AI,
burst forth in November of 2022,
with the launch of ChatGPT.

GPT is a system for predicting
the next word based on
the previous words,
by using a massive model
of the probability
that one word will follow another.

The breakthrough was that the
size of the model is enormous.
(The category name,
Large Language Model, LLM,
is an understatement.)
They include a large percentage
of everything ever written.



What are designers doing with data and AI?

Connor Upton has suggested **a taxonomy of AI techniques:**

See
Computer Vision (CV)
Facial Recognition
Activity Recognition
Detection and Segmentation
Classification
Image Search
Scene Understanding
Visual question answering
Storytelling

Read
Natural Language Processing (NLP)
Text Analysis
Entity recognition
Relationship extraction
Sentiment analysis
Topic segmentation and recognition
Language understanding
Language generation
Questions answering
Automatic summarization

Hear
Digital Signal Process (DSP)
Audio processing
Digital signal processing
Digital image processing
Sonar, radar, sensor processing
Speech recognition
Speech to text

Touch
Robotics
?

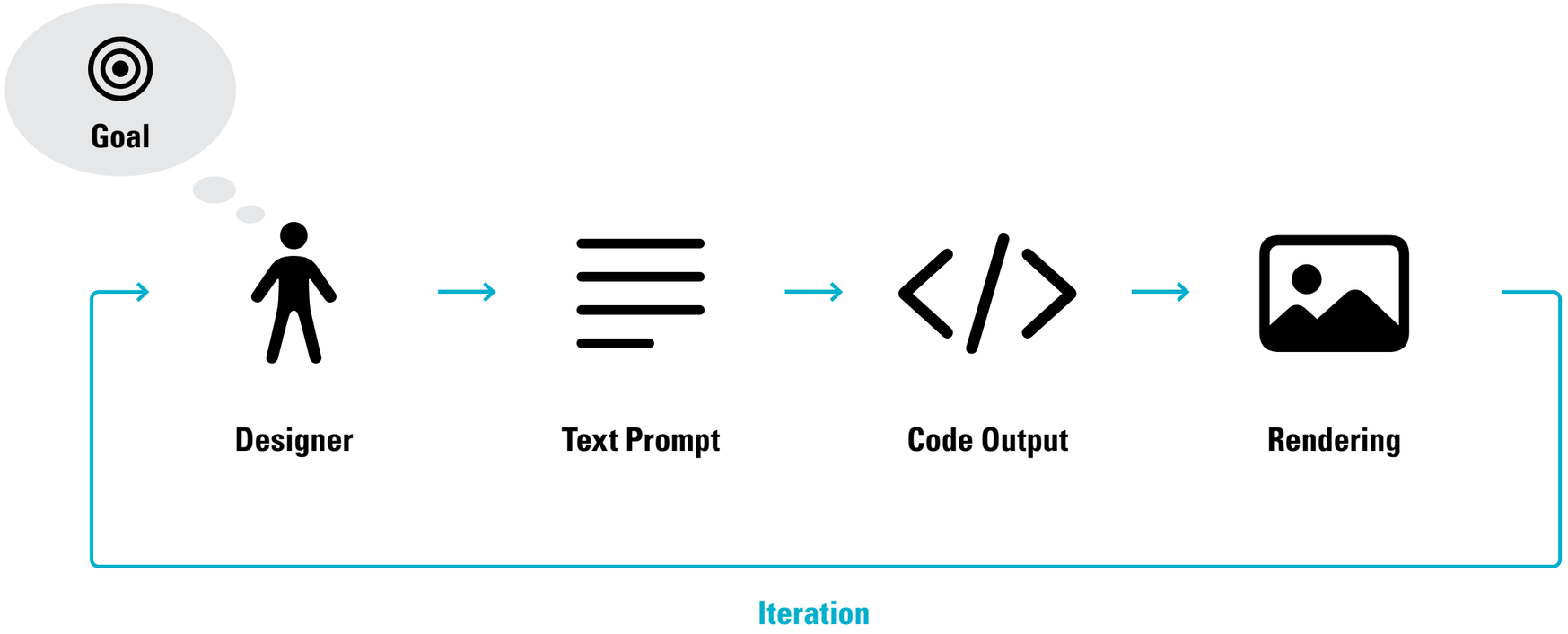
Recommend
Connection + Prediction
Graph Analysis
Simulation
Optimization
“People you may know…”
“Other movies you may enjoy…”
“Customers who bought this also bought…”
“Similar images…”
“Best route to take…”
“Weather forecast for next week…”

Create
Generative AI
Computational Creativity

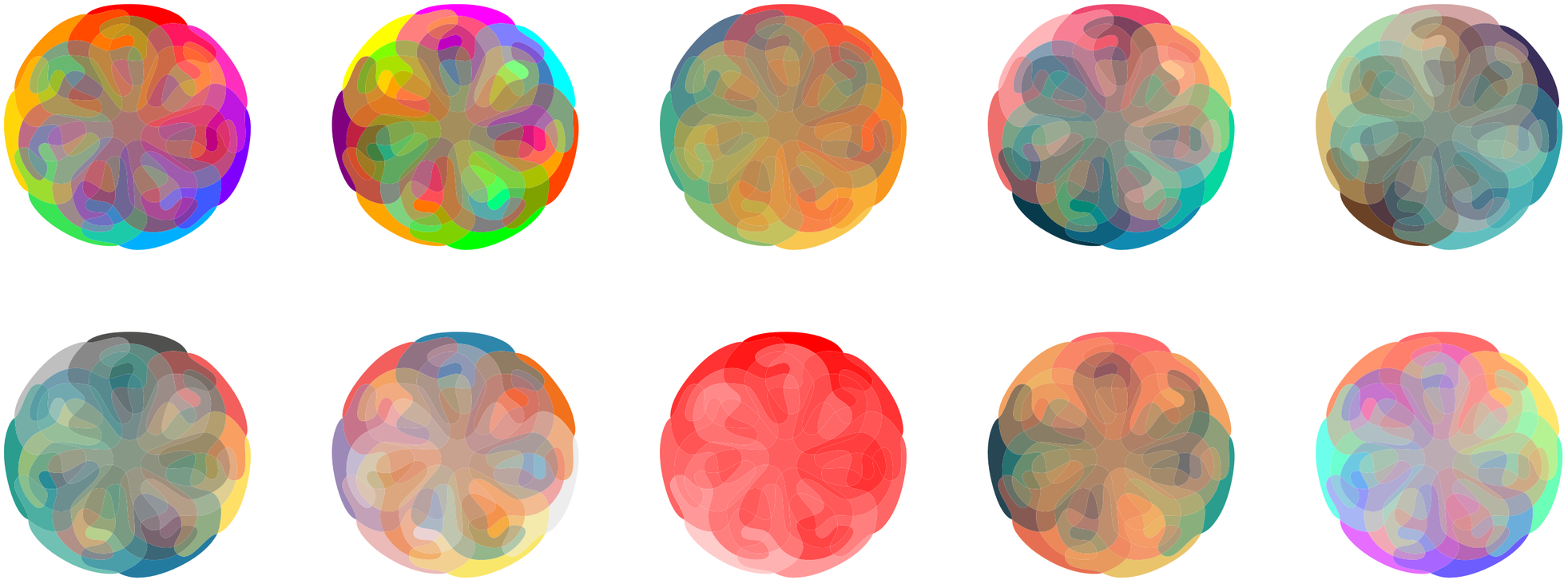
Text-to-image Gen AI preceded ChatGPT.
As yet, there are few compelling uses for design practice.

However, OpenAI and others are hard at work on **text-to-video.**
Friends who have seen research projects report being shocked.
And text-to-audio is already astonishing.
Generating realistic talking animated figures may be in reach.
In a year or two or three, this technology will open **a new medium.**

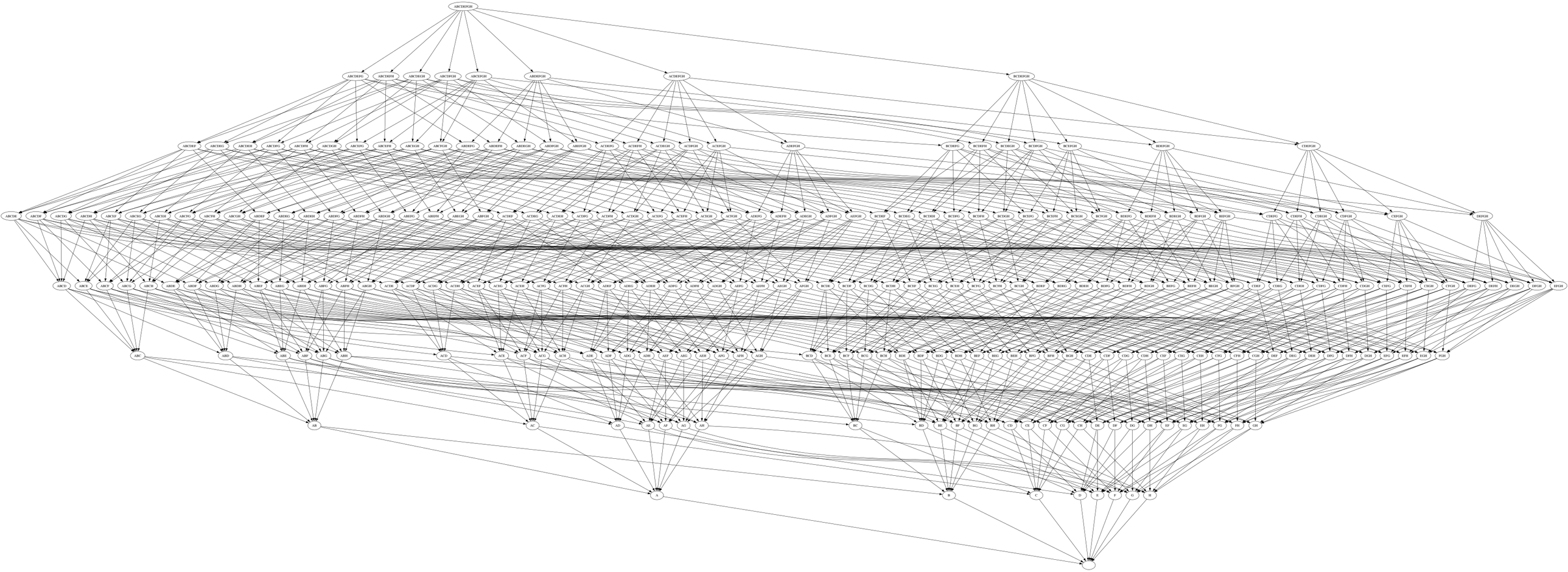
What's exciting — and practical today — is **text-to-code:** designers using an LLM as an assistant to help write code, which then generates images.



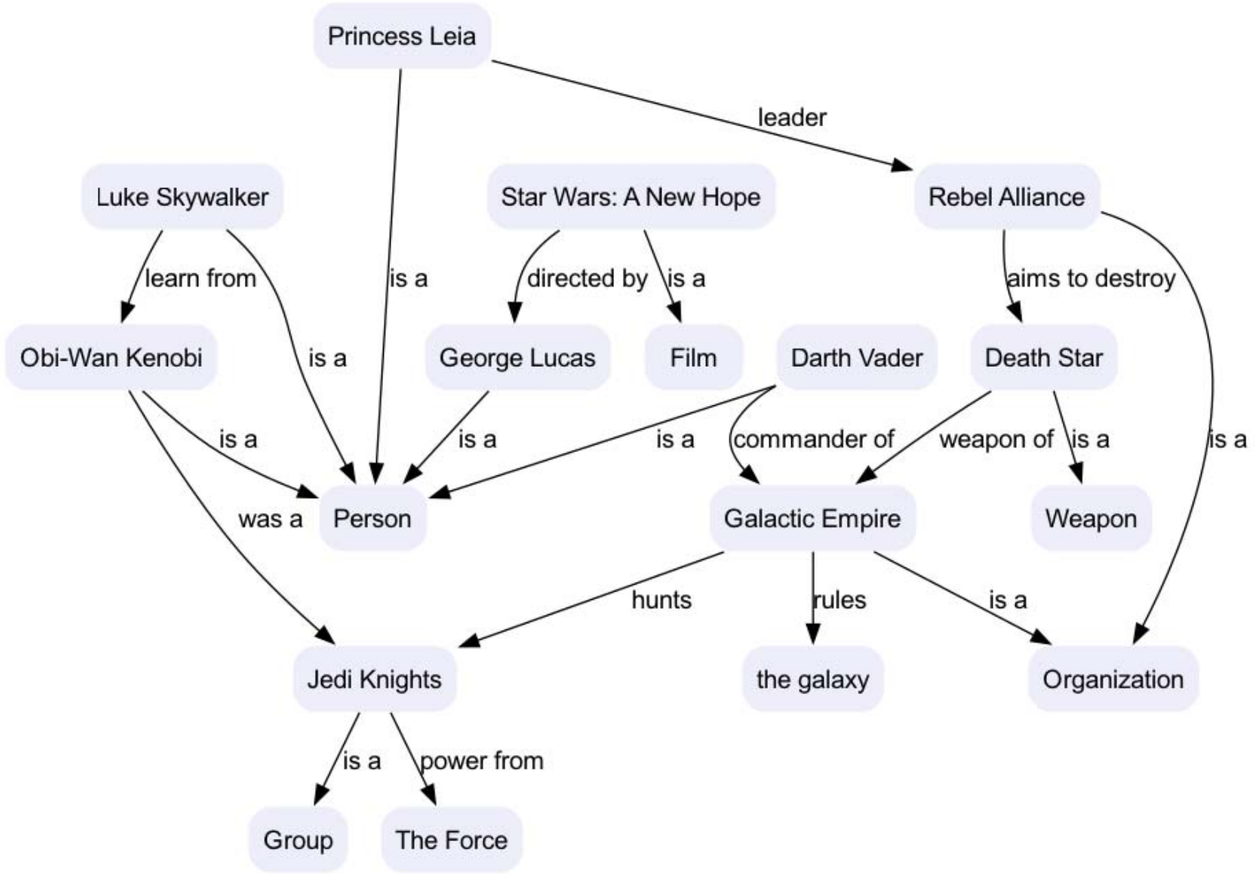
This **logo color transformation** was generated by Jake Sheiner, with coding assistance from GPT.



This **8-set Hasse diagram** was generated by Jabari Jenkins, with coding assistance from GPT.



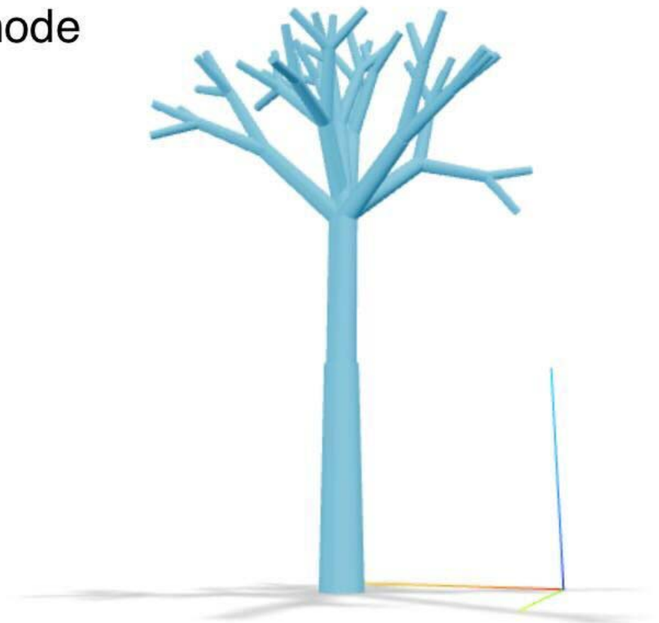
This **concept map** was generated by Jorge Arango, with coding assistance from GPT4.o and GraphGPT.



"Star Wars (film)" by LLMapper • This is an AI-generated concept map. It likely has errors and is published solely for educational purposes.

This **parametric, 3D model** of a tree with branches was generated by Zach Dive,
with a prompt that asked GPT to use recursion.

try this: make a recursive tree with randomly alternating between 2 and 3 branches per node



What’s next?

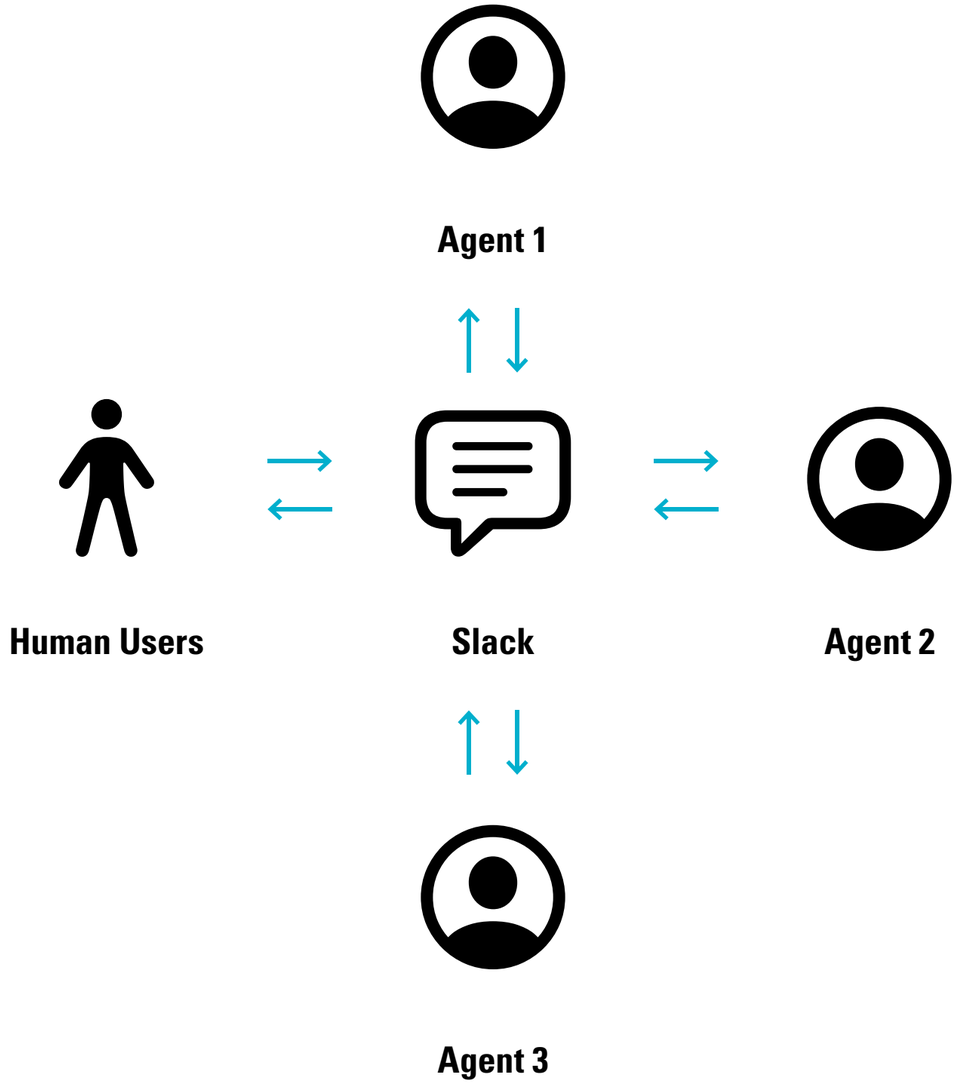
“Intelligent agents” are beginning to emerge — collections of prompts that direct LLMs to perform certain roles.

For example:

- Transcribe this recording (voice-to-text)
- Summarize the transcript
- Format for a note for a medical record
- Review the note for compliance
- Write an alert explaining the issue
- Convert the alert to speech

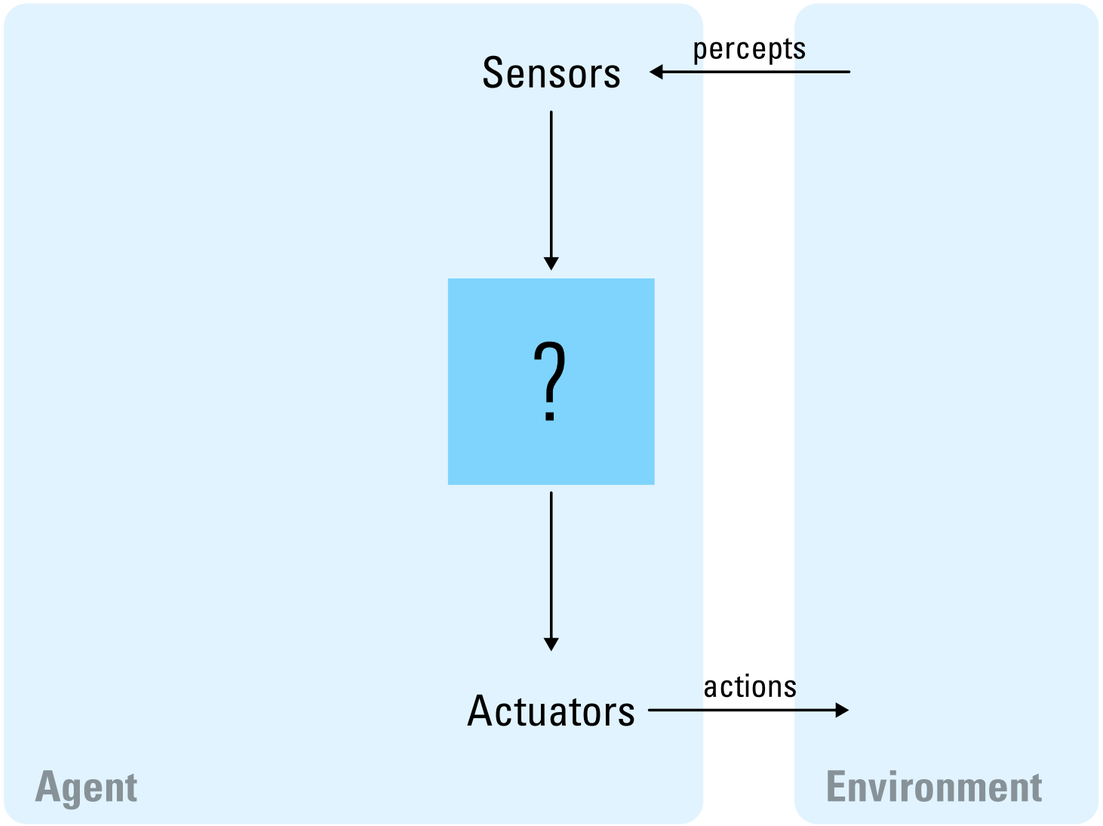
What’s more astonishing:

These intelligent agents talk to each other, in code or even on Slack.



Russell and Norvig have suggested **a taxonomy of intelligent agents.**

1. Simple reflex agents
2. Model-based reflex agents
3. Goal-based agents
4. Utility-based agents
5. Learning agents



An ‘intelligent agent’ can be defined as an entity that:

1. perceives its environment
2. takes actions autonomously in order to achieve goals

an intelligent agent might also:

3. improve its performance with learning or acquiring knowledge

For more information:
https://presentations.dubberly.com/Intelligent_Agents_and_Multi-Agent_Systems.pdf

Use of LLMs is **evolving quickly;** already we are on a 5th “generation”.

0. **Code-based** interaction (before ChatGPT)
1. Interaction via a **“chat” window**
2. Building complex prompts with **text snippets**
3. Adding a wrapper that keeps a **history**
4. RAG (Retrieval Augmented Generation)
   using a **prompt library and vector database** (e.g., LangChain and Pinecone)
   to focus the system on known content and reduce errors
5. GraphRAG, adding a **knowledge graph**

Technology evolves in layers, which form stacks.
Seemingly overnight.....**a new Data-AI stack has emerged.**

The new stack is a platform for enhancing services,
which are already components of product-service ecologies.
At this moment, it looks like so-called intelligent agents
will be built into everything,
just as we saw with microprocessors, sensors, and networks.

We still don't know what to call this.
Data- and AI-enabled agentic-product-service ecologies is long,
but it describes key elements.

Data- and AI-enabled agentic-product-service ecologies

enabled by

Intelligent Agents

enabled by

Predictions

enabled by

AI (CV, DL, ML, NLP, etc.)

enabled by

Data

enabled by

Technology Infrastructure
Cloud Computing Services
Networks
Microprocessors, Computers, Sensors, Phones

What might this mean?

Data and AI are revolutionizing software,
disrupting the economy,
and creating the need and space for **a new type of design.**

- Data and AI are already **tools** for designing.

- Data and AI are becoming the **material** out of which designers make services.

- Data and AI are on the verge of becoming a new **medium** as well.

The future is not fixed.

These are still early days;
now is the time to **experiment.**

Designing for “data- and AI-enabled agentic-product-service ecologies” brings new **responsibilities** and requires reassessing **principles.**

We are responsible for what we build and for the language we use, which bring into being the world in which we live together.

That suggests that we:

- Make sources, processes, and arguments **transparent** (Cf., Horst Rittel)
- Act so as to increase the number of real **choices** available (Cf., HvF)
- Prefer **augmentation** over automation
- Act with **mindfulness** engaged
- Take care with the **language** we use

Shelley Evenson has suggested **principles:**

Human's Rule.
What a person says goes.

We must design for the unintended consequences
of how people will react and be proactive in combatting it
by enabling humans to do everything the agents can do
and can override everything.

Agents are embedded in the workspace.

We need to think of the communication in the context of the work,
not as a sidebar chat. The agents are invited into the space
where humans work, not siloed from it
which means the agents learn from human actions —
giving quality data to the LLMs, but also maintaining that Humans rule.

Agents are accountable.

They show their work, are transparent about their sources
and level of confidence. The interface helps people
develop a mental model of how the technology is working.
No black boxes.

Above all—Amplify human creativity and skill building

Utilizing the vast knowledge accessible to the agents,
we can present humans with opportunities they may not have considered.
Finding ways to encourage curiosity to explore paths not taken.
No deskilling.

Perhaps a fitting way to end is with **a reminder** from Aristotle's *Ethics.*

"Every art [techne]
and every inquiry [methodose],
and likewise every action [praxis]
and choice,
seems to aim at some good,
and hence it has been beautifully said that
good is that at which all things aim [goal]."

— Aristotle: *"Nicomachean Ethics,"* Book 1, Chapter 1, Line 1

Even as “software is eating the world,”
the key question for designers remains:

What is good?

Neither data nor AI can tell us.
Only we can answer the question.

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