Emergence of Universal Engineering

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About Me

Pavel Loskot joined the ZJU-UIUC Institute as Associate Professor in January 2021. He received his PhD degree in Wireless Communications from the University of Alberta in Canada, and the MSc and BSc degrees in Radioelectronics and Biomedical Electronics, respectively, from the Czech Technical University of Prague. He is the Senior Member of the IEEE, Member of ACM and APSIPA, Fellow of the UKHEA, and the Recognized Research Supervisor of the UKCGE. He was elected the IARIA 2025 Fellow.

In the past nearly 30 years, he was involved in numerous industrial and academic collaborative projects in the Czech Republic, Finland, Canada, the UK, Turkey, and in China. These projects concerned wireless and optical telecommunication networks, genetic regulatory circuits, air transport services and renewable energy systems. This experience allowed him to truly understand the interdisciplinary workings, and crossing the disciplines boundaries.

His current research focuses on mathematical and probabilistic modeling, statistical signal processing and machine learning for multi-sensor and longitudinal data in biomedicine, computational molecular biology, and wireless communications.

My background

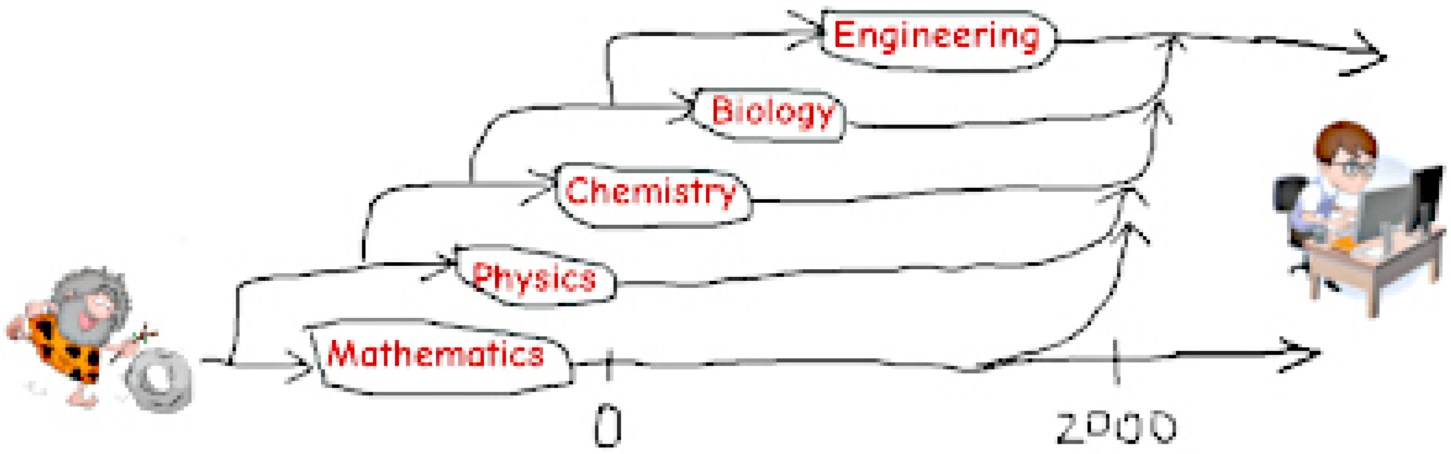
Research interests

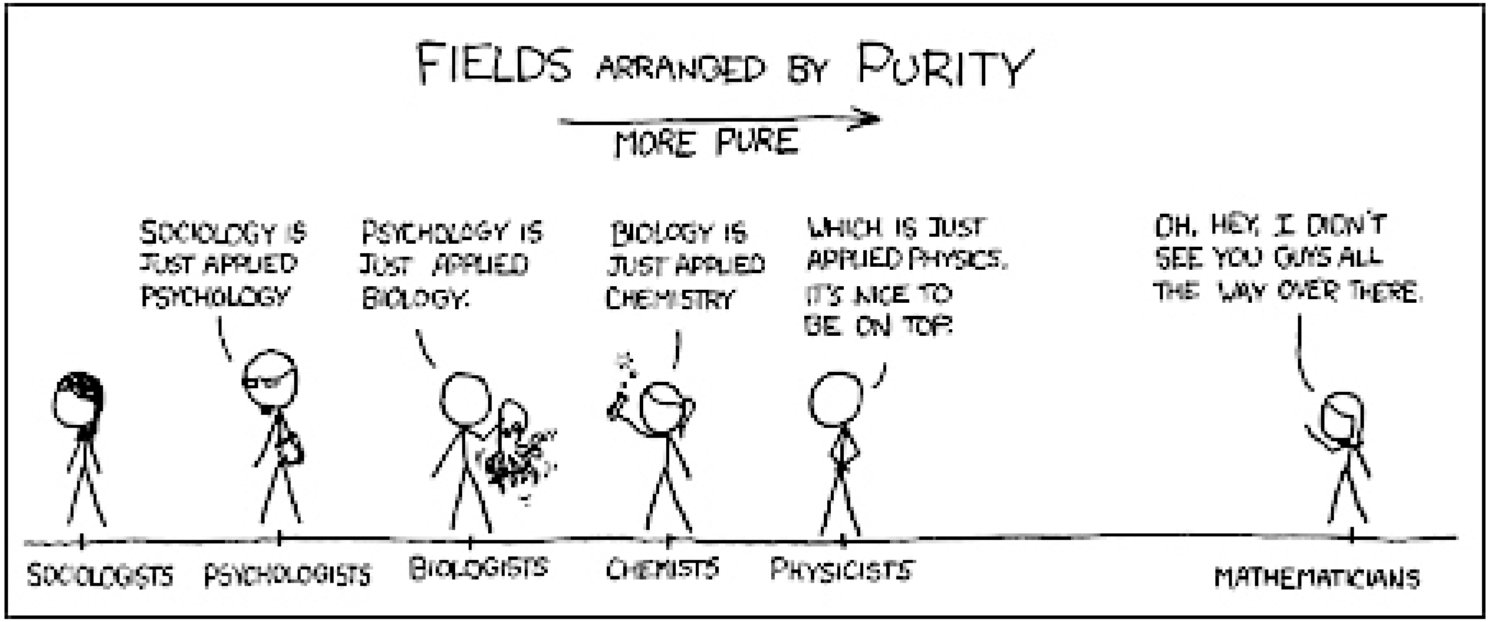
- statistical signal processing
- classical machine learning
- mathematical modeling
- statistical and causal inference
- computer experiment design

Outline

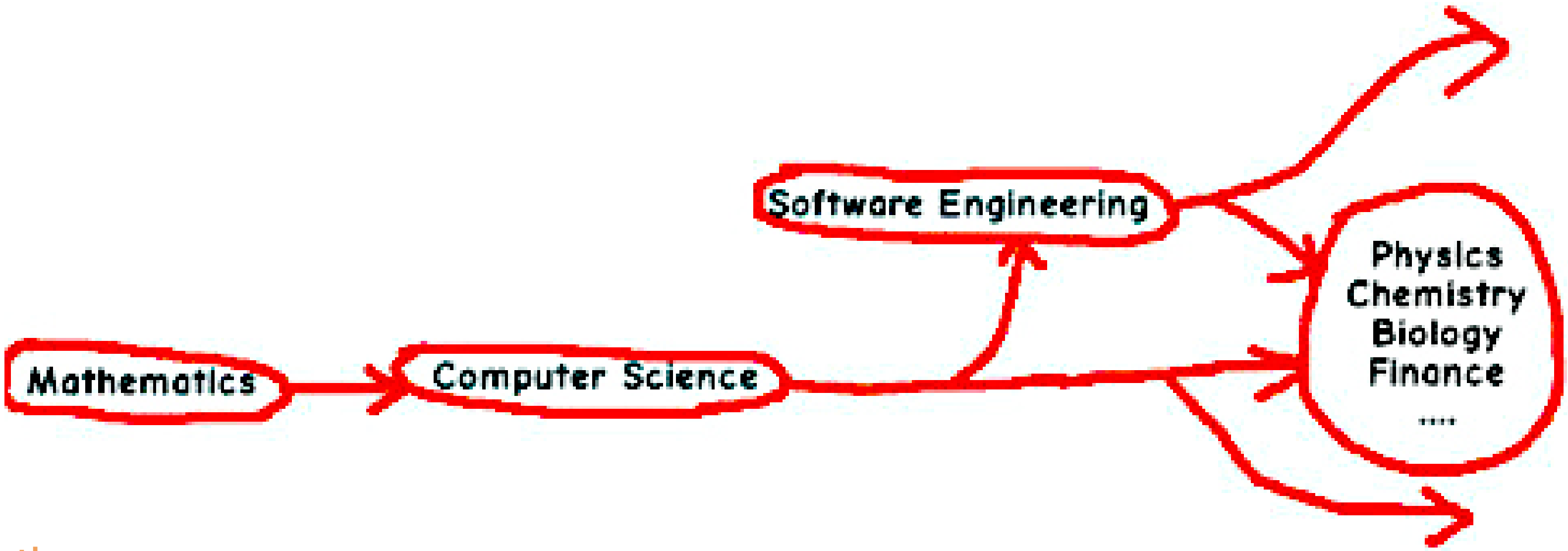
1. Evolution of disciplines and research methods
2. Fundamental laws and limits of engineering designs
3. Model-based, universal, and experimental methods
4. Recent developments in (engineering) research

Evolution of Scientific Disciplines





Evolution of Computer Science



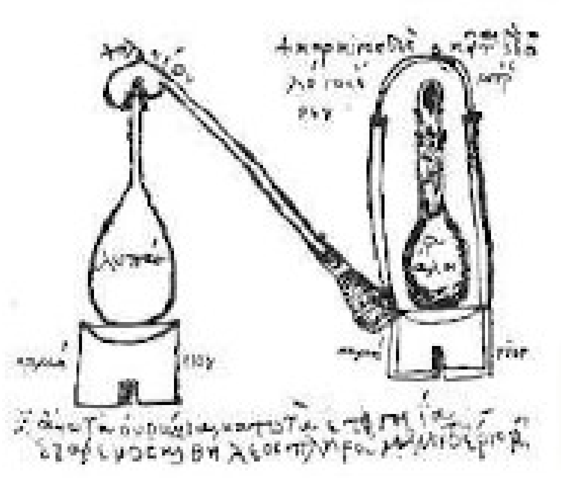
Evolution

- emerged from mathematics during/after WWII
- split into traditional (theoretical) and software based in 1990's

Take-over of other disciplines

- telecommunications and network science in 1990's
- many (all) other disciplines after 2000
  → everyone is working with data and mathematical models
  → machine learning
  → semantic information and representations
  ...

Evolution of Research Methods



Problems of simplicity (1600-1800)

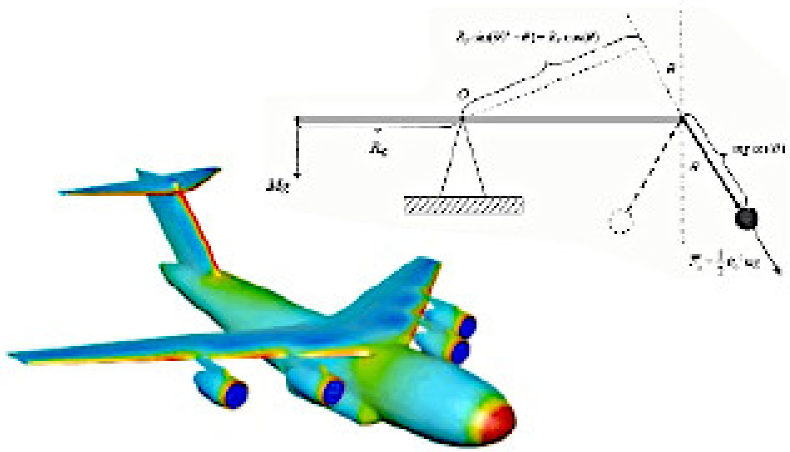
- simple physical models of measurable quantities

Problems of disorganized complexity (1900-1950)

- more complex but with well defined behavior

Problems of organized complexity (since 1950's)

- embracing all factors influencing whole system



Experimental science (until 1700's)

- observations and experiments

Theoretical science (until 1940's)

- mathematical analysis

Computational science (until 2000)

- computer simulations

Big data science (after 2000)

- data collection and knowledge mining

Mathematical abstractions (past decade)

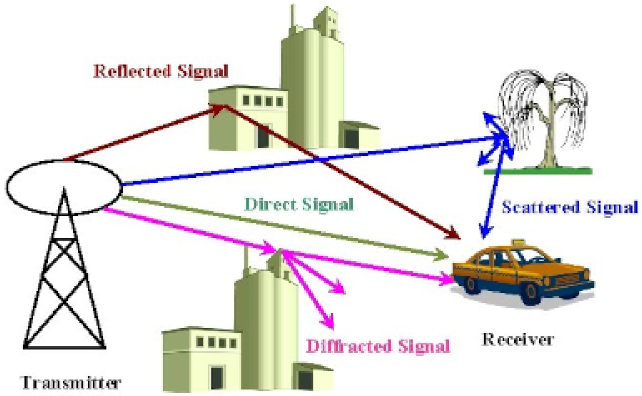
- information granularization and modularization

Fundamental Laws of Engineering Designs

1. Dealing with uncertainty

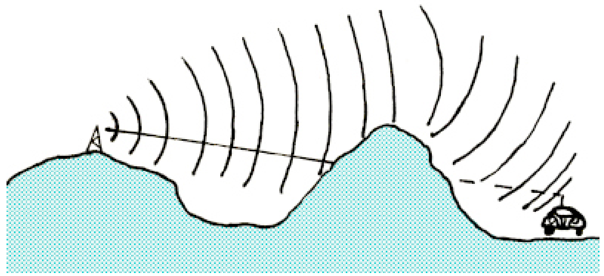
- world appears noisy, systems behave randomly
- diversity is the only way for reducing uncertainty
  → many different and sometimes unexpected forms

2. Dealing with signal distortion



- most distortions can be perfectly removed,
  if there is no random noise
- noise is the key limiting factor of performance
- other factors are implementation complexity and costs
  → how to replace noisy semiconductors?

3. Physical laws can be bent



- engineering hacks stretching limits of physical laws
- example
  → non-line-of-sight wireless communication systems

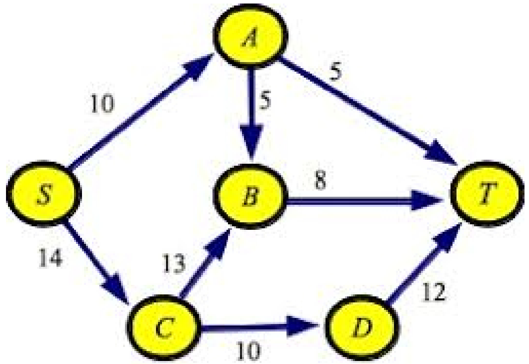
Fundamental Laws of Engineering Designs (cont.)

4. Scaling-up systems

- the only way is to make systems distributed
- increases flexibility, but also complexity
  → requires orchestration protocols

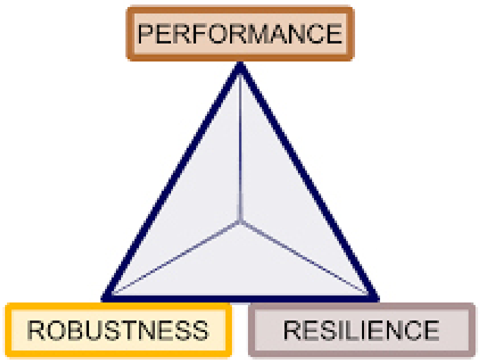
5. Dealing with flows

- vital for operation of distributed systems
- emergence of hubs in networks
- common issues
  → congestion, routing, capacity



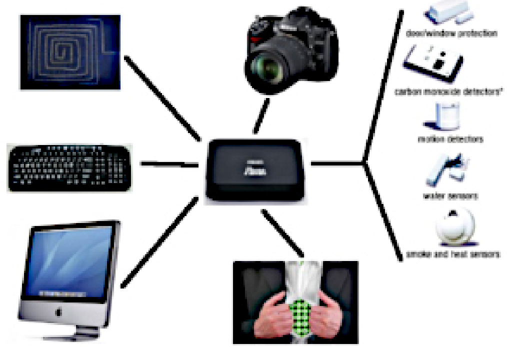
6. Solutions must be robust

- best performance means nothing in practice
  → need good enough guaranteed performance
- operational under wide range of conditions
  → inefficient to have different solutions for different conditions



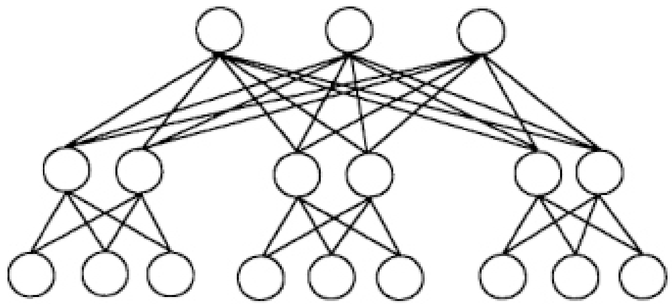
Fundamental Laws of Engineering Designs (cont.)

7. Distributing and pooling resources



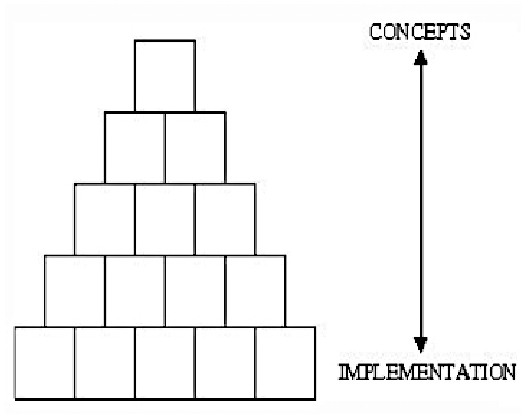
- first distribute, then pool resources
- very flexible, endless opportunities for innovations
- design systems as well as solutions to problems

8. Avoid extremes cases



- fully distributed system
  → too complex to organize
- centralized (monolithic) system
  → not flexible, single point-of-failure

9. Concepts ≠ their implementations

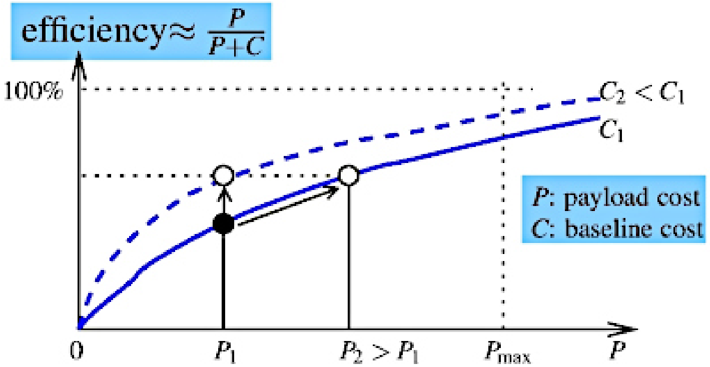


- strictly separate concepts and their implementations
  → one concept can have multiple implementations
- greatly misunderstood principle

Fundamental Limits of Engineering Designs

1. Energy limits

- idle systems consume energy to maintain readiness
  → energy efficiency is always below 100%
- energy is conserved but constantly changes forms
  → to reduce energy, do useful work as fast as possible

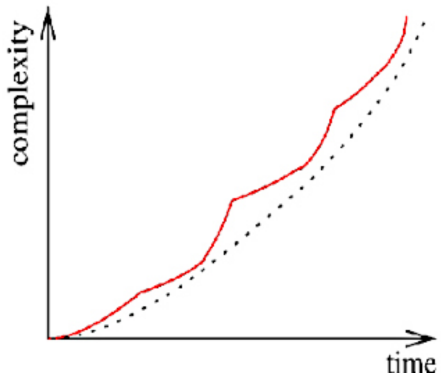


2. Structural limits

- systems conserve their structure
  → maintain structural continuity
- adaptive systems
  → speed of change is limited

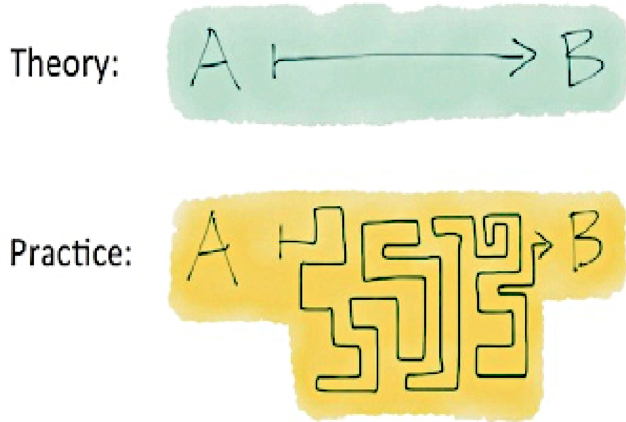
3. Complexity limits

- evolution is mechanism of complexity growth
  → the growth is highly non-linear
- complex systems evolve randomly
  → problems cannot be solved



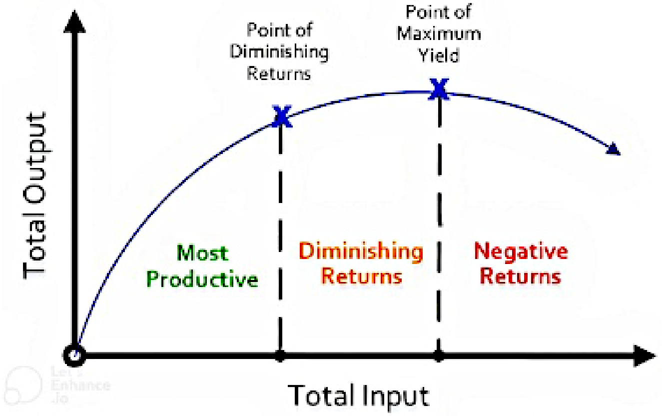
Perfect systems do not exist. Sustainability is an illusion.

Fundamental Limits of Engineering Designs (cont.)



4. Practice eventually meets theory

- practical approach
  → improving existing systems
- theoretical approach
  → evaluate the ultimate limits
- these approaches eventually meet



5. Diminishing returns

- any design strategy will eventually fail
- due to interactions among system components
- further (modest) improvements require
  → exponentially more resources, energy, costs, ...

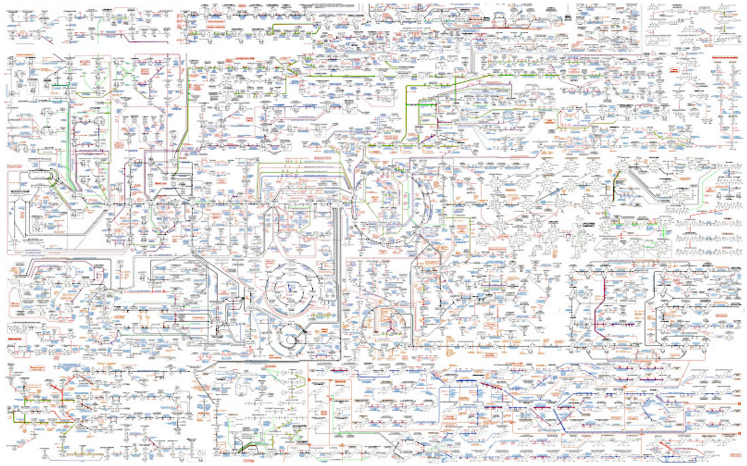
6. Humans are driven by natural instincts

- any resources will be discovered and used
- capacity and offerings must constantly grow
  → sustainability does not exist

Complex Adaptive Systems

Working with complex systems

- far beyond complicated (size irrelevant)
- complexity increases in time (evolution)
- short-long-term non-linear interactions
- unpredictable behavior
  → self-organization, emergence, chaos



Tools and methods

- vastly different scales
  nano → micro → meso → macro
- usual methods not efficient, or not work at all
  → trial&error, divide&conquer
- limited mathematical models
- effect of interventions
  → delayed, not obvious, costly

Wicked problems

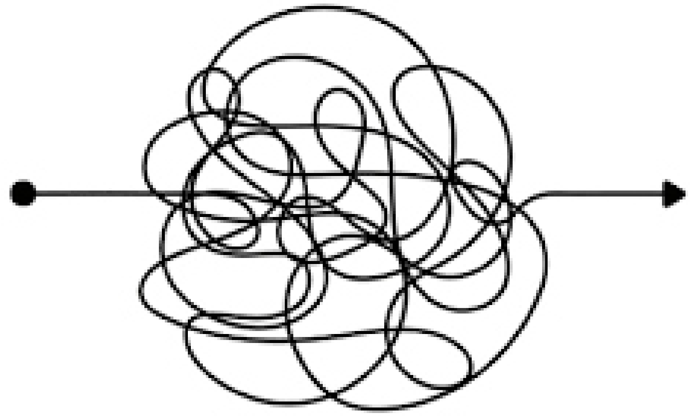
- to alter behavior of complex systems
- can never be completely solved
  → solutions only better or worse
- solving one problem
  → creates or reveal more problems
- causes and effects are not obvious
  → unpredictable outcomes

Kaisler and Madey, CAS: Emergence and Self-Organization, 2009.

Complexity is (Very) Bad

Complexity cycle

1. complex systems run into complex problems
2. complex problems require complex solutions
3. complex solutions increase complexity
4. go to step 1



Complexity kills robustness

- more things can go wrong
- more opportunities for deliberate damages
- it is more likely something goes wrong

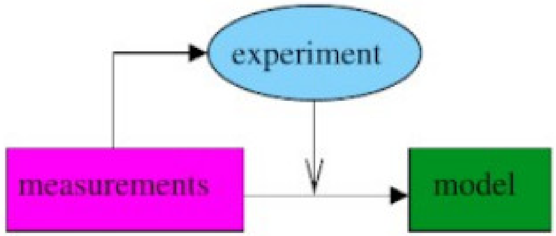
Typical case

- increasing system capacity makes this system more complex
  → e.g. to provide more services to more users
- when something goes wrong (which is now more likely)
  → cost of damages greatly increased

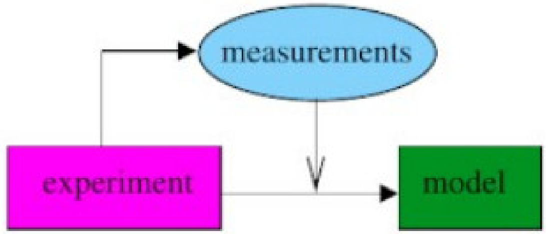
Do we have a choice to avoid complexity cycle?

Limits of Mathematical Modeling

Forward/backward modeling

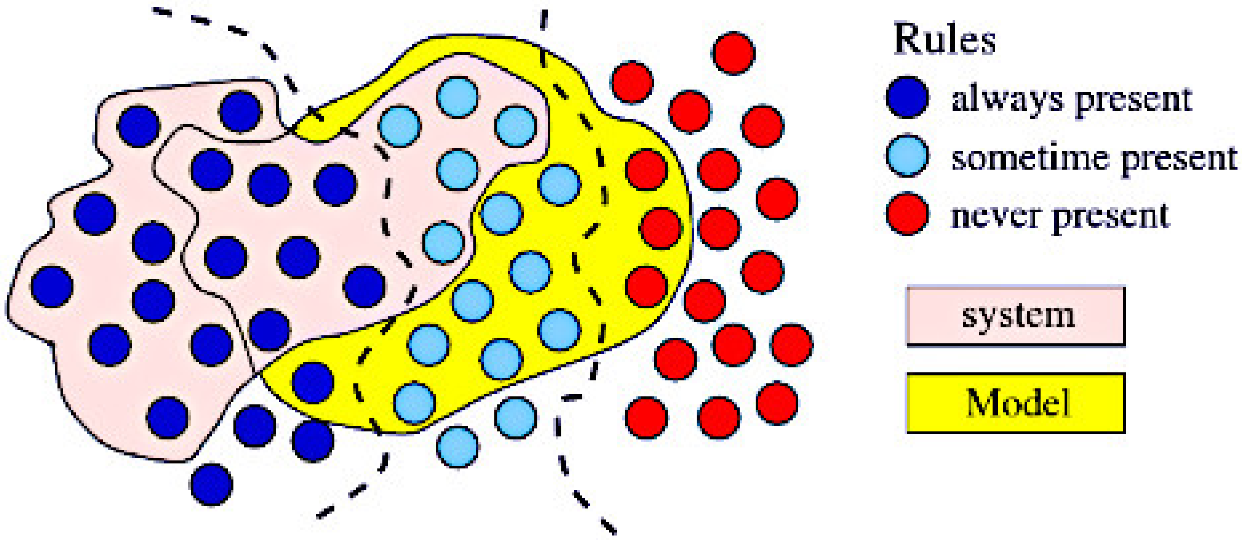


available measurements constrain possible applications



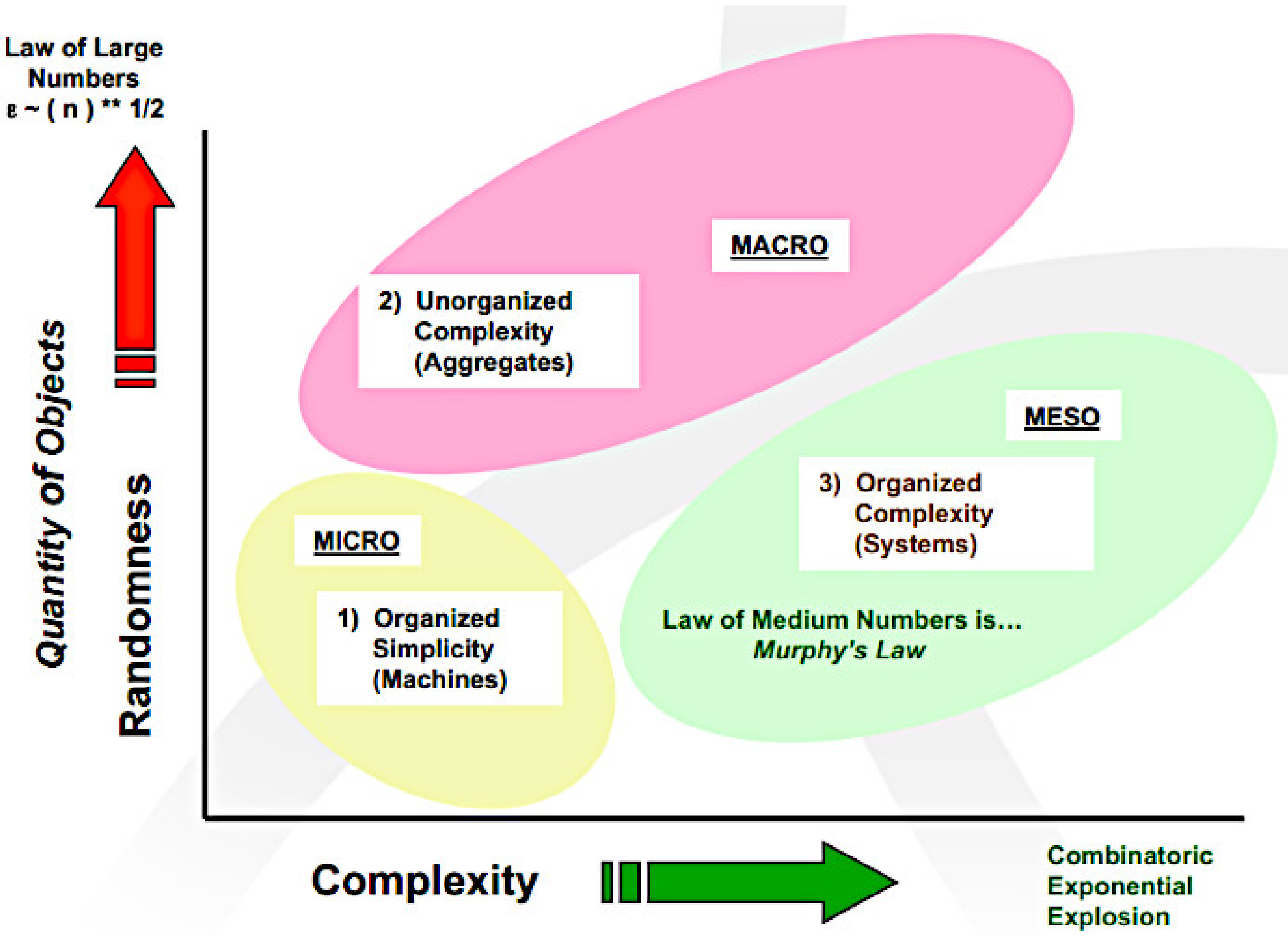
application determines required measurements

Capturing physical laws



... we don't know what we don't know

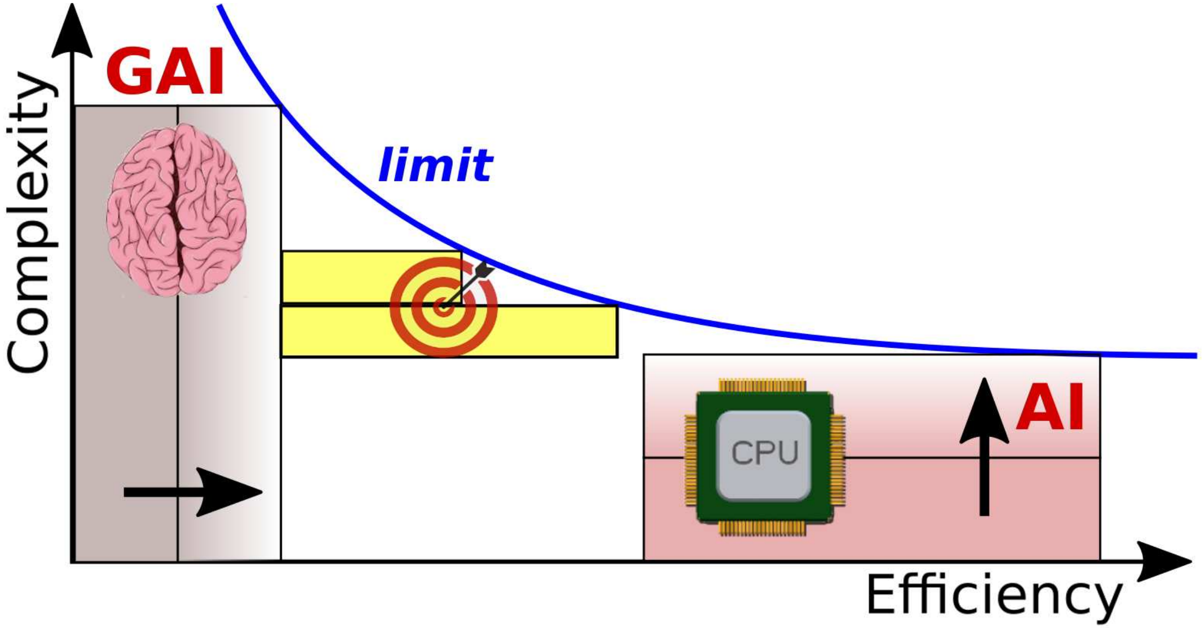
Model Granularity



Models are simple

- locally, but emergent macro-properties difficult to deduce
- globally due to averaging that occurs at large scales

Computational Problems



general		specific
probabilistic		deterministic
learning-based	Methods	rule-based
abstract		quantitative
algebraic		computational
symbolic		numerical

Can every problem be reduced to a computational problem?

How to Causally Explain the World?

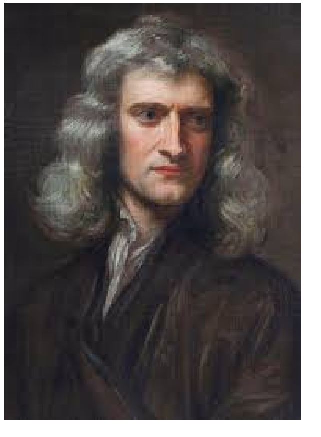
Understanding the world

- can we derive causal explanations from data?
  → causal inference

Johannes Kepler (1571–1630)

- the first data scientist
  → data provided by astronomer Tycho Brahe
- predicted planetary trajectories
  → symbolic regression

Isaac Newton (1643–1727)



- Newton's laws
  → physical laws involving gravity
- explained why planets have orbits
  → scientific description needs "why"

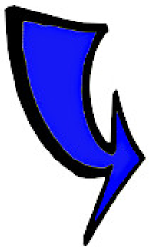
Model-Based vs. Sample-Based Methods

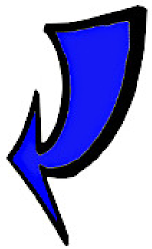
Model-based methods

- high adaptability and explainability
- numerically very efficient
- defined optimality
- model requires assumptions

Sample-based methods

- no model assumptions
- can have very good performance
- numerically (much more) expensive
- sensitivity to training mismatch

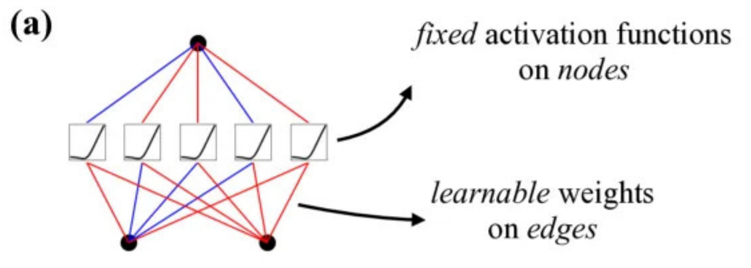
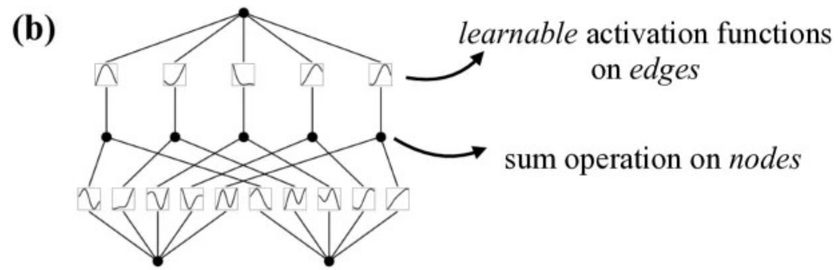
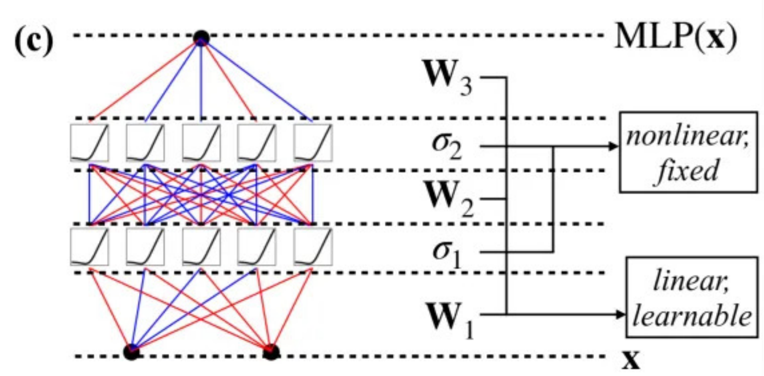
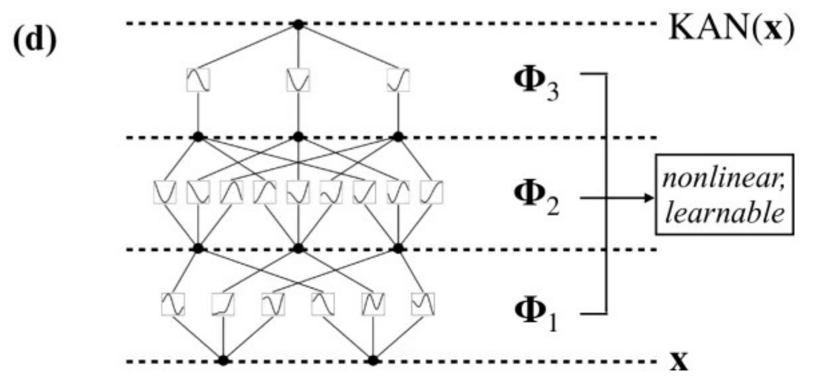




Hybrid methods

- can achieve good performance trade-offs
- fewer model assumptions
- reduced numerical complexity while offering adaptability
- required training can be a limiting factor
- more complex design

Universal Function Approximators

<table>
<tr><td>Model</td><td>Multi-Layer Perceptron (MLP)</td><td>Kolmogorov-Arnold Network (KAN)</td></tr>
<tr><td>Theorem</td><td>Universal Approximation Theorem</td><td>Kolmogorov-Arnold Representation Theorem</td></tr>
<tr><td>Formula (Shallow)</td><td>$f(\mathbf{x}) \approx \sum_{i=1}^{N(\epsilon)} a_i \sigma(\mathbf{w}_i \cdot \mathbf{x} + b_i)$</td><td>$f(\mathbf{x}) = \sum_{q=1}^{2n+1} \Phi_q \left(\sum_{p=1}^{n} \phi_{q,p}(x_p) \right)$</td></tr>
<tr><td>Model (Shallow)</td><td>
</td><td>
</td></tr>
<tr><td>Formula (Deep)</td><td>$\mathrm{MLP}(\mathbf{x}) = (\mathbf{W}_3 \circ \sigma_2 \circ \mathbf{W}_2 \circ \sigma_1 \circ \mathbf{W}_1)(\mathbf{x})$</td><td>$\mathrm{KAN}(\mathbf{x}) = (\mathbf{\Phi}_3 \circ \mathbf{\Phi}_2 \circ \mathbf{\Phi}_1)(\mathbf{x})$</td></tr>
<tr><td>Model (Deep)</td><td>
</td><td>
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Ziming Liu et al., KAN: Kolmogorov-Arnold Networks, arXiv:2024.1975v4, June 2024.

Universal Research Methods

George Polya's problem solving techniques (1945)

1. If you are having difficulty understanding the problem, draw a picture.
2. Assume some solution and see what you can derive from that (go backward).
3. If the problem is abstract, try examining a concrete example.
4. Try solving more general problem first.

Inventor's paradox

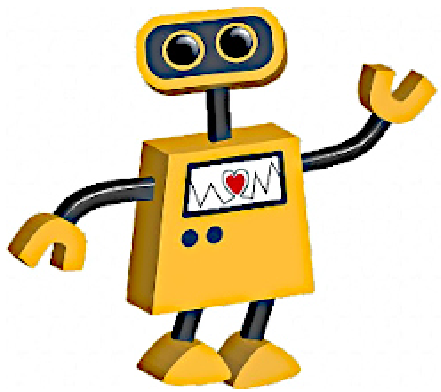
- more ambitious plans may have more chances of success

Translations and generalizations

- aim: imitate successful ideas/products/papers/objects
- how: assume different or more general context

How to generate new ideas

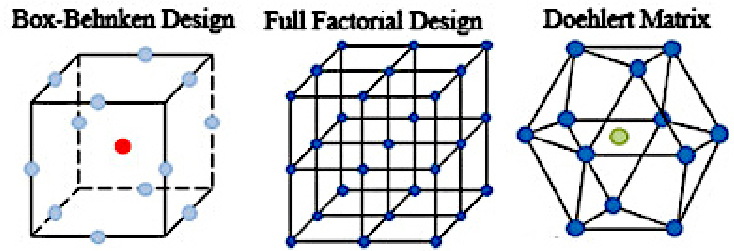
- combinatorial innovations
  → ability to make not-so-obvious connections
- how to search combinations effectively?
  → systematically to allow discovery of unlikely pairings



Combinatorial Innovations as Experiment Design

Experimental procedure

1. formulate a null hypothesis
   → existence of a causal association (explanation)
2. choose factors to randomize/block/control
3. collect data from experiments
4. statistically accept/reject null hypothesis



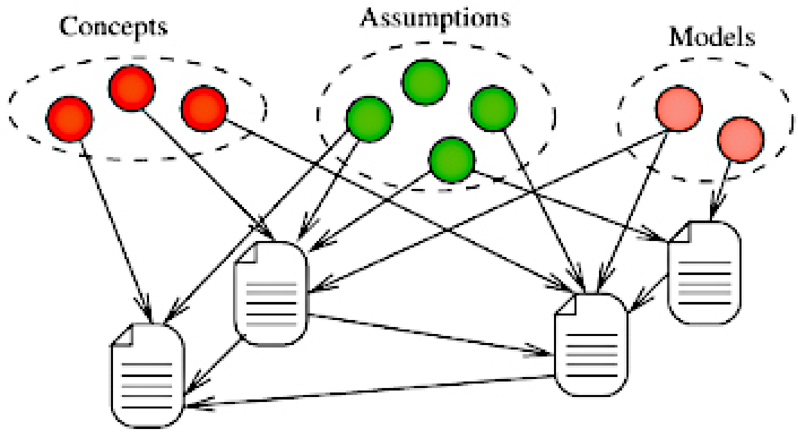
Key considerations

- efficiency (time, costs, data)
  → brute force methods
- accuracy, confidence, reproducability
- effects must be measurable

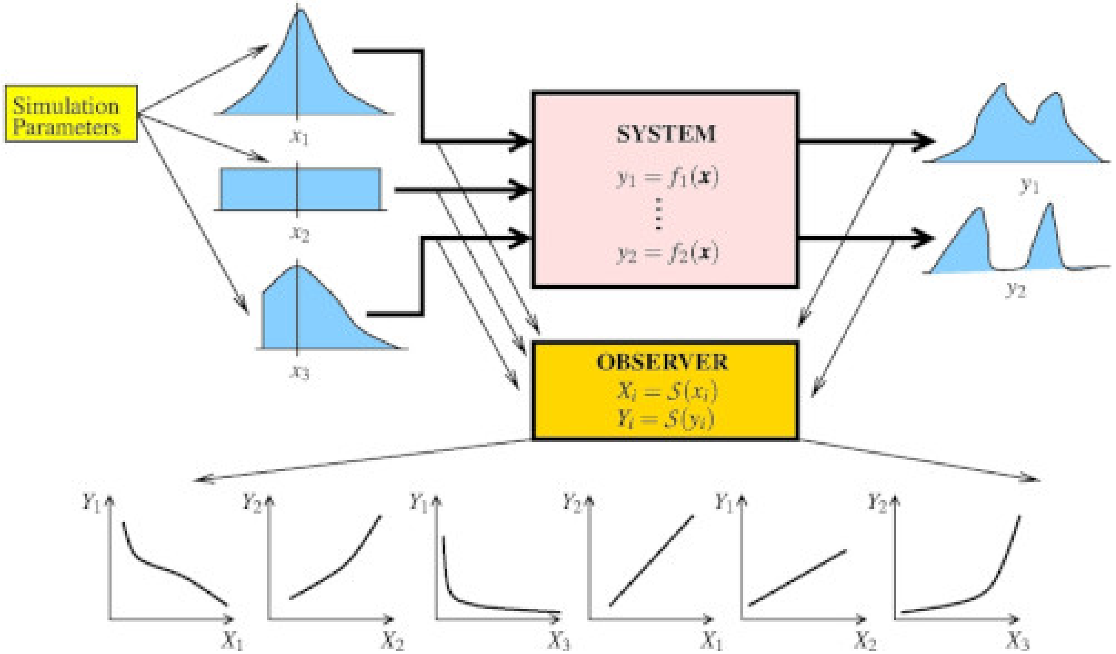
FACTOR	LABORATORY	FIELD
Environment	Artificial	Realistic
Control	High	Low
Reactive error	High	Low
Demand artifacts	High	Low
Internal validity	High	Low
External validity	Low	High
Time	Short	Long
Number of units	Small	Large
Ease of implementation	High	Low
Cost	Low	High

Basic strategies

- model-based designs
- factorial and block designs
- *sequence of short experiments or one long?*



Computer-Based Experiments



Pros

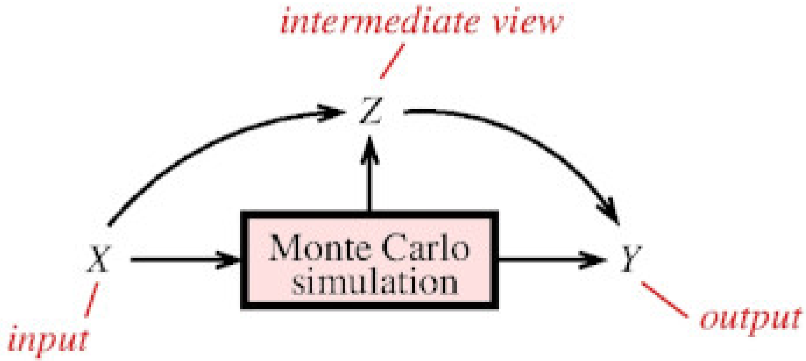
- general, no assumptions, fast setup
- low-cost, failing is cheap, may explore larger spaces
- compare models, test assumptions, identify bottlenecks and limits
- maximize information gain, perform what-if analysis
  → much easier and cheaper than lab and field experiments

Cons

- may take long time (when to stop?)
- lack of explainability, reproducability
- may be biased
  → variance-bias trade-off
- eventually must be validated
- different errors
  → choice of models & assumptions
  → implementation of algorithms

Computer-Based Experiments (cont.)

Intermediate views



- direct causal paths: $X \to Z$, $Z \to Y$, $X \to Y$
- backdoor path between Z and Y: $Z \leftarrow X \to Y$
  $\to$ X is common cause (confounder)
- conditioned on X: block backdoor path and allow causal inference
  $\to$ *key for creating explainable complex models (e.g. machine learning)*

$$\Pr(Y,Z,X) = \Pr(Y|Z,X)\,\Pr(Z|X)\,\Pr(X)$$

$$\Pr(X|Y) = \frac{\Pr(Y|X)\Pr(X)}{\Pr(Y)} \qquad \Pr(Z|Y) = \frac{\Pr(Y|Z)\Pr(Z)}{\Pr(Y)} \qquad \Pr(X|Z) = \frac{\Pr(Z|X)\Pr(X)}{\Pr(Z)}$$

$$\Pr(Y|X) = \sum_{Z} \Pr(Y|X,Z)\,\Pr(Z|X) \qquad \Pr(Y|Z) = \sum_{X} \Pr(Y|X,Z)\,\Pr(X|Z)$$

Research Production vs. Consumption

Research production

- became much easier and faster
  → wasteful of resources
- mostly descriptive
  → lacking depth and credible explanations
- knowledge is a commodity
  → *researchers are information operators*

Research distribution

- aggressive marketing and attention grabbing
- unresolved conflicts of interest
  → reviewing research papers

Research consumption

- new results or better use of existing results?
- how to choose results that matter?

} *newly emerged problems*

Research Strategies for Engineering

Rigorous research

1. interpretable: can explain why it works
   → how to verify explanations?
2. reproducible: equivalent of usable
   → reproducing core idea vs. incremental improvements?

Minimum viable products (MVPs)

- only satisfy necessary requirements
  → continuous development
- sufficient and necessary objectives
  → mutual dependency
- *can we afford MVPs in research?*

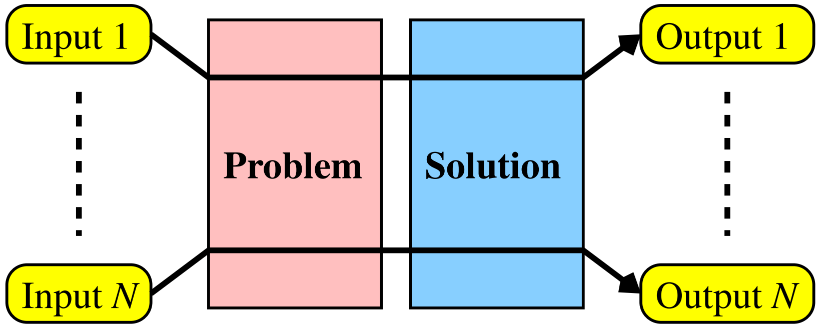
Key considerations

- when to declare research outcomes as final
  → allow beta versions? version control?
- is rigorousness limiting progress?
  → excluding viable alternatives that are less rigorous
- best performance of robustness?
  → in practice, needs to latter

Towards Meta Research

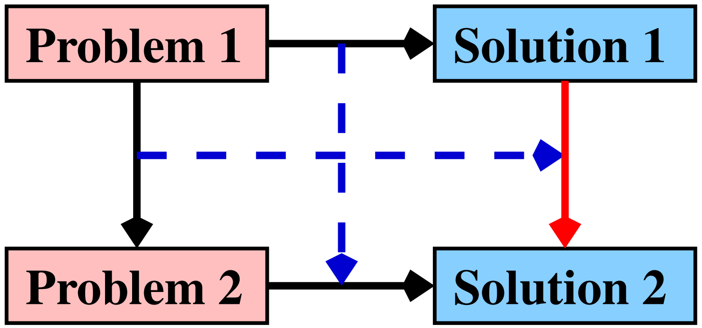
Most of today's research

- a general problem
  → a known solution
- multiple instances of this problem
  → still the same solution



Research on research

- problem reductions
  → standard strategy in computer science
- solution reductions (red arrow)
  → why not to consider these too?
- *reductions of reductions* (blue arrows)

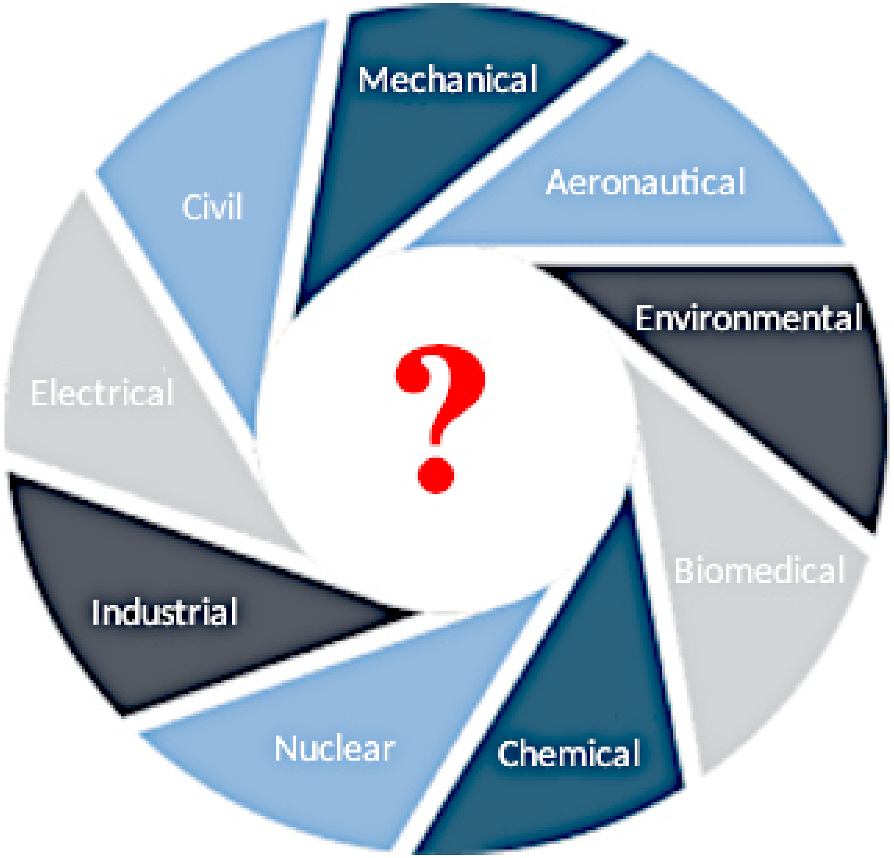


Practical questions

- how to reuse research methods and problem-solving strategies?
- what research methods and problem-solving strategies are most general?
- how to adapt/evolve research methods and problem-solving strategies?

research methods ⊂ problem-solving strategies

Towards Universal Engineering



Things in common**?**

- building and analyzing models
  → data-driven methods
- experimental strategies
  → testing hypotheses

Things that are different**?**

- performing experiments
  → manipulating physical objects
- domain expertise
  → physical laws

Industry vs. Academia

Universities

- negligible resources
- time to think
- can afford risks
- peer evaluation

v.s.

Industry

- plentiful resources
- no time to think
- risk avoidance
- customer evaluation

In the past 20 years

- equipment have become affordable
- all major software (including AI) innovations done in industry
  - → test-driven development
  - → testing automation
  - → refactoring
  - → continuous integration and delivery
  - → Transformers and LLM

... universities are playing a catch-up

Take-Home Messages

Mathematical modeling

- model trade-offs
  → accuracy vs. expressiveness vs. efficiency
- composition of hierarchical and concurrent models
  → knowledge granularization
- validating and explaining models
  → data-driven universal models (deep learning)

Research methods

- equivalents of minimum viable product?
- how much research needs to be rigorous?
- can we ignore impact of social networks?
- how to improve search of combinatorial spaces?

Knowledge

- became a commodity, researchers are knowledge operators
- how to choose knowledge that matter?
  → research on research

Thank you!

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