

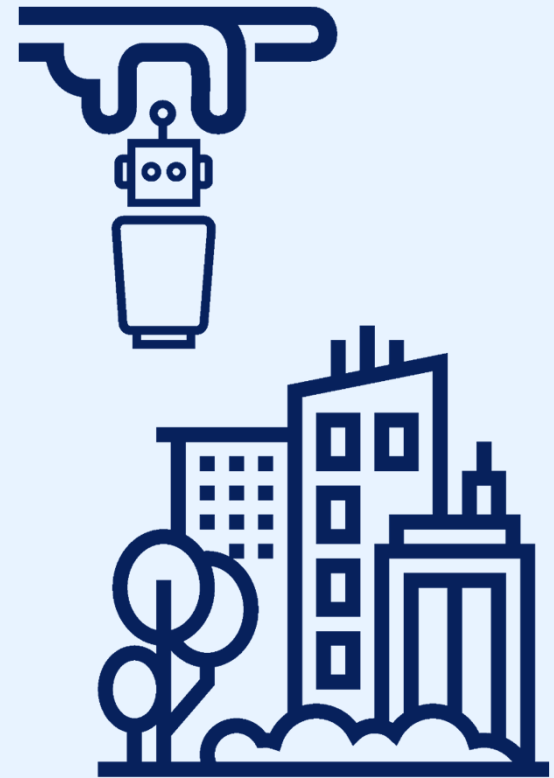
Potential to Augment Urban Planning ~~with AI~~ With Intelligence— in Responsible Ways

Steven Miller

Professor Emeritus of Information Systems, SMU
and Hybrid Intelligence Advisory

Urban Sustainability R&D e-Symposia
Urban Analytics Webinar

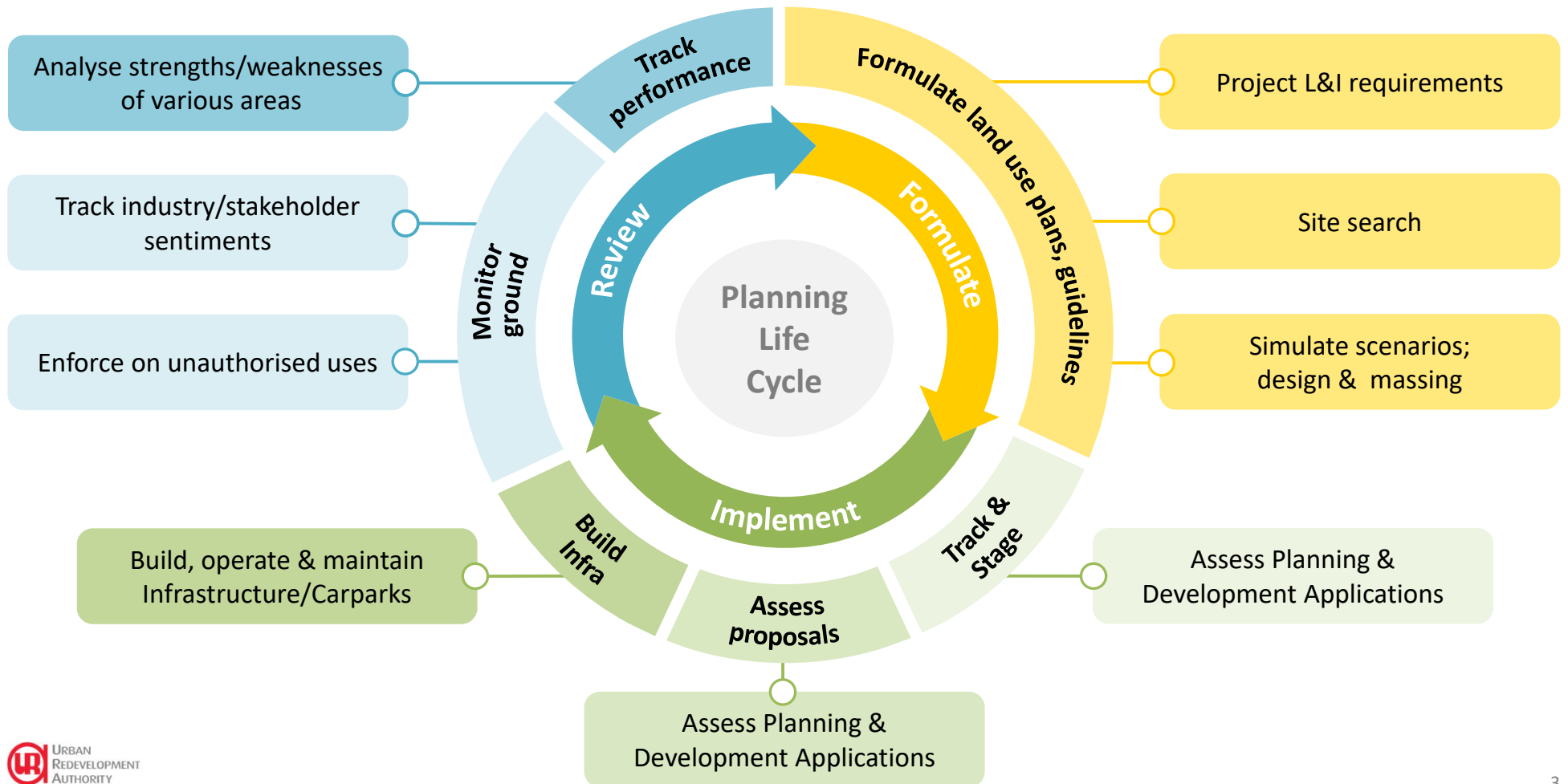
26 November 2021



Agenda

- 1. The urban planning domain**
- 2. What do we mean by AI and intelligence (including learning)**
- 3. Augmenting Urban Planning with AI as well as with other mindsets, methods and toolsets**
 - Experimentation in Policymaking
 - Forecasting and Future Scenario Analysis – addressing the Inherently uncertain and/or unknowable
- 4. Using Artificial Intelligence in responsible ways**
 - By proceeding with FEAT/FAT/FATE related efforts
 - By recognizing limitations and strengths of AI vis-à-vis humans

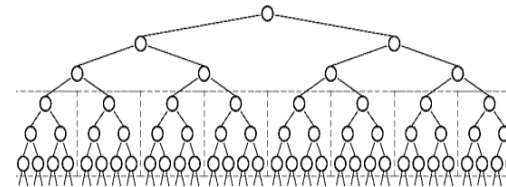
The Urban Planning Domain- Using URA's Planning Life Cycle Model



What is AI: Computational systems (machines) capable of SEARCHING, REASONING, and LEARNING

SEARCHING for solutions

- Choosing a winning action by looking ahead and considering the outcomes of different possible action sequences
- Dealing with combinatorial complexity- the rapid explosion in the number of combinations to explore as the number of alternatives increases
- Looking further ahead



LOGICAL REASONING with certain knowledge

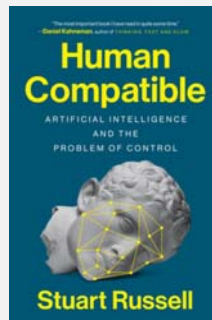
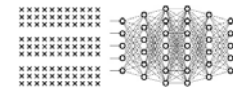
PROBABILISTIC REASONING with uncertain information

LEARNING from experience

Learning general rules and principals from a single example, or a very small number of examples

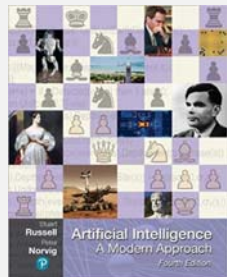
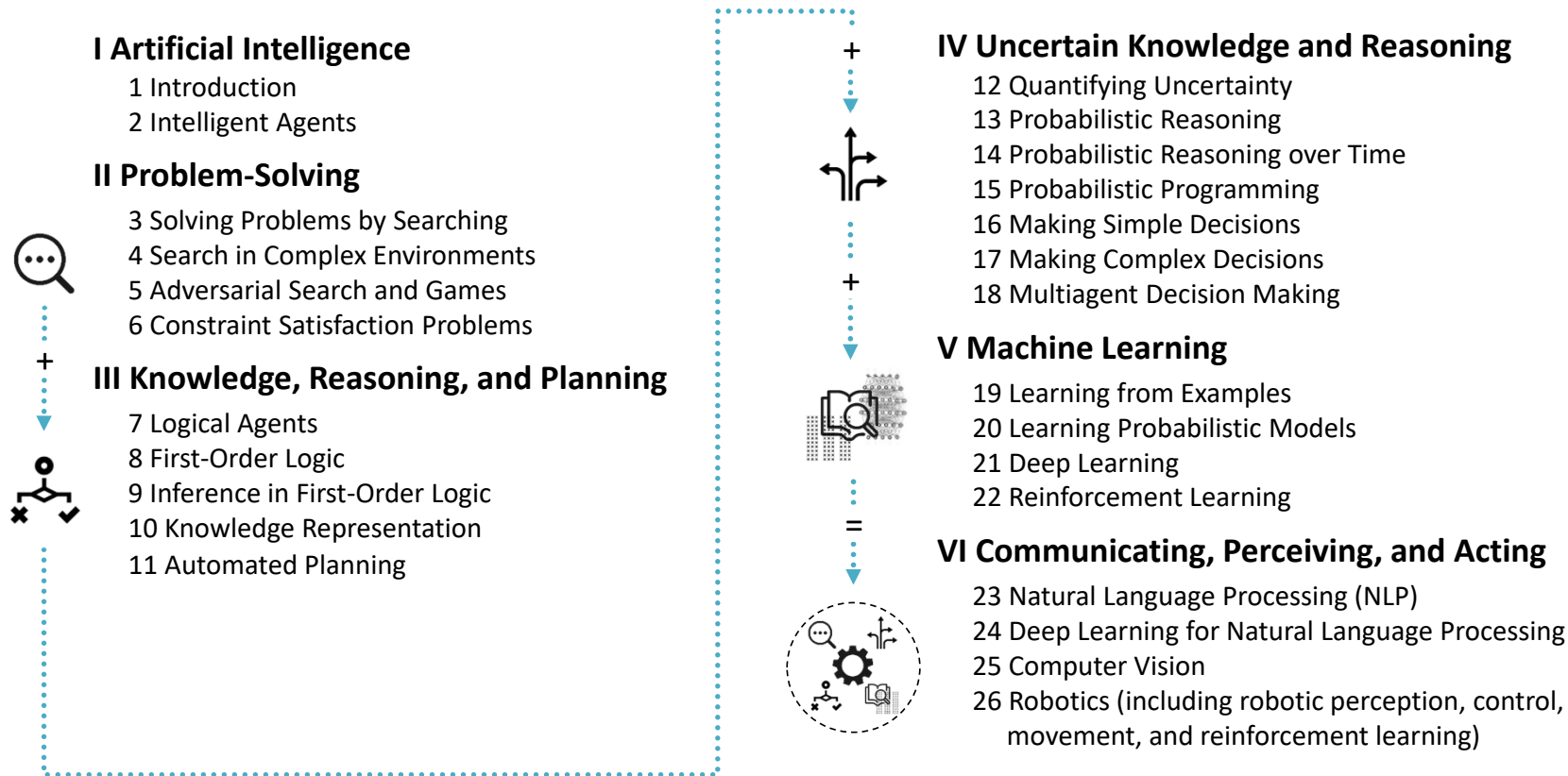


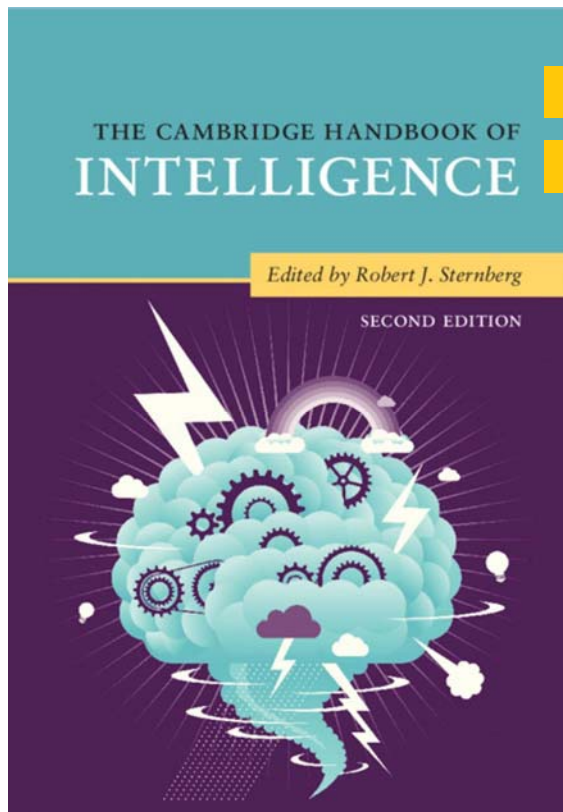
Learning correlation patterns from a very large number of examples



Adapted from Stuart Russell, *Human Compatible: AI and the Problem of Control*. Viking Press, 2019.

The table of contents of *Artificial Intelligence: A Modern Approach, 4th Edition*, April 2020, by Stuart Russell and Peter Norvig. Published by Prentice Hall.





Volume I

Volume II

2nd Edition.
Published in 2020 by
Cambridge
University Press.

50 chapters by many
authors and co-
authors.

1249 pages across
both volumes.

“


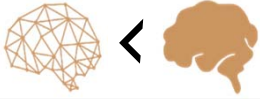
Ironically, intelligence is at the same time the most successful construct in psychology with regards to measurement while it has become famous for its reputation of being impossible to define.

...apparently, the lack of definition of intelligence does not prevent its measurement from being useful and having predictive value....

”

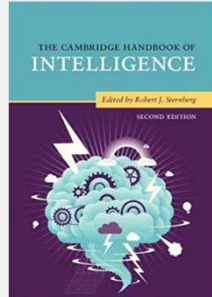
Chapt 5, pg 70, “An Alternative View on the Measurement of Intelligence and Its History”, Paul De Boeck, et al.

Comparing Human Intelligence and Machine Intelligence Based on Sternberg's Theory of Successful Intelligence

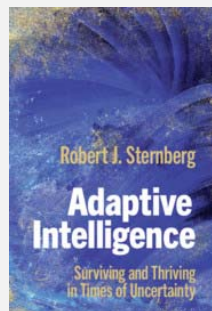
<p>Creative Intelligence</p> <p>GENERATE novel and useful ideas.</p> <ul style="list-style-type: none"> • create • design • invent • imagine • suppose 	<p>Analytic Intelligence</p> <p>ASCERTAIN the quality of ideas and analysis.</p> <ul style="list-style-type: none"> • compare and contrast • evaluate 	 
<p>Wisdom-based Intelligence</p> <p>ENSURE a COMMON GOOD through the mediation of positive ethical principles.</p>	<p>Practical Intelligence</p> <p>APPLY ideas and plans; CONVINCe others of their value.</p> <ul style="list-style-type: none"> • Use • Apply • Implement • Employ • Contextualize 	<p>Sources:</p> <p>www.robertjsternberg.com/successful-intelligence</p> <p>and</p> <p>Robert Sternberg, "The Theory of Successful Intelligence," chapter in <i>The Cambridge Handbook of Intelligence</i>, edited by Robert Sternberg and Scott Barry Kaufman, 2011, Cambridge University Press.</p>



2020

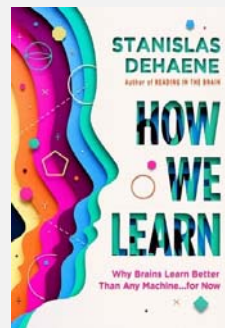
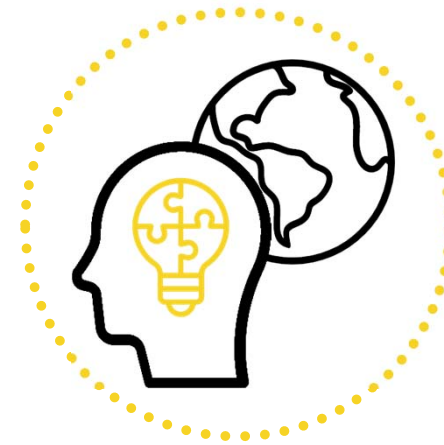


2021



How We Learn (Book): Relevant Summary Statements

- **What does “learning” mean?**
 - To learn is to form an internal model of the external world.
- **Seven key ideas that lie at the heart of present-day machine learning algorithms and that may apply equally well to our brains (though implemented in different ways) —**
 - Seven different definitions of what “learning” means:
 1. Learning is adjusting the parameters of a mental model.
 2. Learning is exploiting a combinatorial explosion.
 3. Learning is minimizing errors.
 4. Learning is exploring the space of possibilities.
 5. Learning is optimizing a reward function.
 6. Learning is restricting the search space.
 7. Learning is projecting a priori hypotheses.

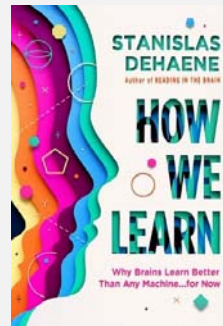
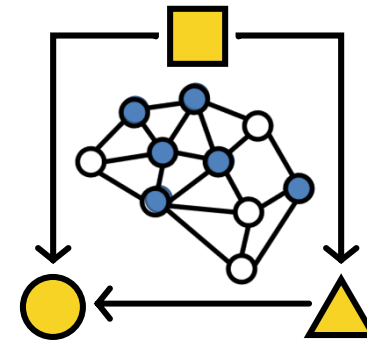


How We Learn (Book): Relevant Summary Statements

What is Artificial Intelligence missing?

Here is a short and probably still partial list of functions that even a baby possesses (and adults as well) that most current artificial systems are missing:

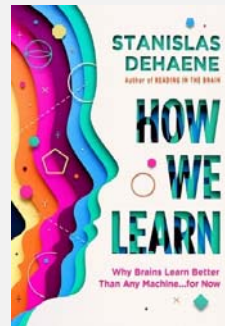
- **Learning abstract concepts.**
 - Humans deploy an unmatched knack for abstraction.
- **Data-efficient learning.**
 - In the field of learning, the effectiveness of the human brain remains unmatched: machines are data hungry, but humans are data efficient.
 - Learning, in our species, makes the most from the least amount of data.
- **Social learning.**
 - Our species is the only one that voluntarily shares information: We learn a lot from our fellow humans through language.
 - Conscious knowledge comes with verbal reportability.
 - Whenever we understand something, a mental formula resonates in our language of thought, and we can use the words of language to report it.



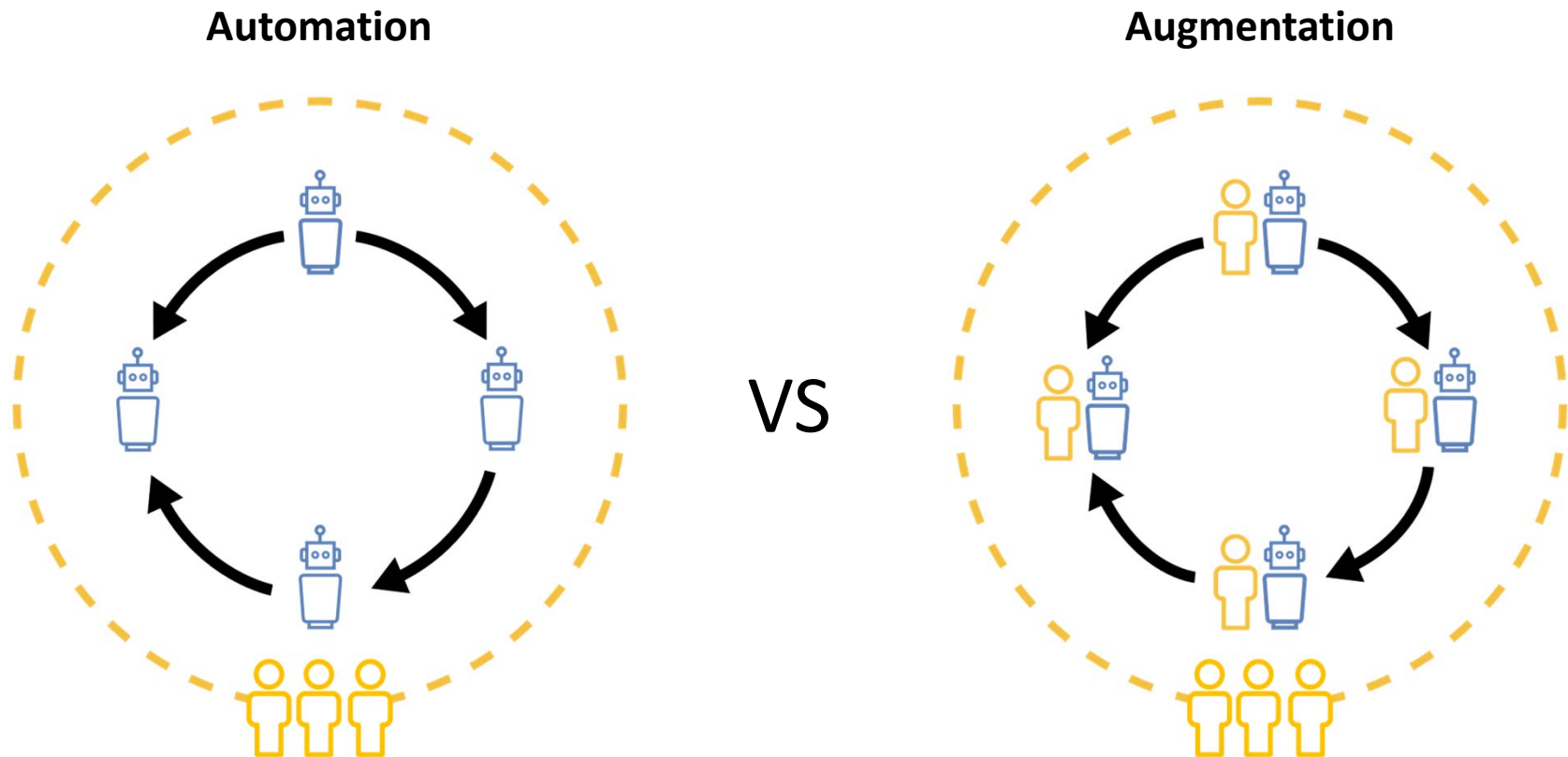
How We Learn (Book): Relevant Summary Statements, con't.

What is Artificial Intelligence missing, continued.

- **One-trial learning.**
 - An extreme case of this efficiency— when we learn something new on a single trial.
 - Some artificial neural networks are capable of storing a specific episode. But what machines cannot yet do well, and that the human brain succeeds in doing wonderfully, is integrate new information within an existing network of knowledge.
 - To learn is to succeed in inserting new knowledge into an existing network.
- **Systematicity and the language of thought.**
 - A particular talent in our brain is the ability to discover the general laws that lie behind specific cases.
 - The human brain manages to extract very abstract principles, systematic rules that it can reapply in many different contexts.
 - Systematicity, the ability to generalize on the basis of a symbolic rule rather than a superficial resemblance, still eludes most current [\(machine-learning\)](#) algorithms.
- **Composition.**
 - Humans can recombine what they learn with other learned skills.
 - In the human brain [\(in contrast to AI systems\)](#), learning almost always means rendering knowledge explicit, so that it can be reused, recombined, and explained to others.
 - Humans can use learning to reason, a logical inference that attempts to capture the rules of a domain.

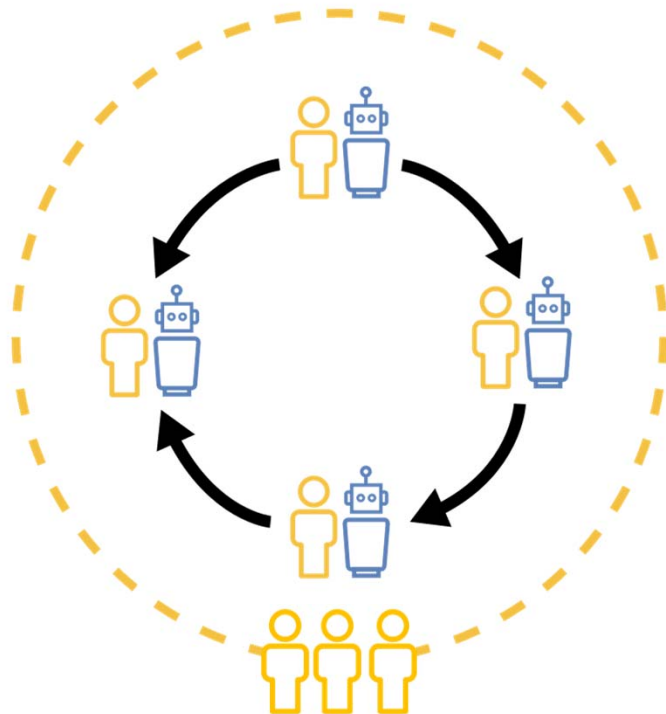


Contrasting Mindsets for Using AI (and other Advanced Tools)



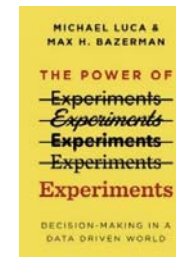
Different Approaches for Augmenting Urban Planning Intelligence

Via Combining Human and AI Intelligence



and

Via Incorporating Other Types of Disciplinary Mindsets, Methodologies and Toolsets



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DOI: [10.23919/JSC.2021.0009](https://doi.org/10.23919/JSC.2021.0009)

Hybrid Predictive Ensembles: Synergies Between Human and Computational Forecasts

Lu Hong, PJ Lamberson, and Scott E Page*



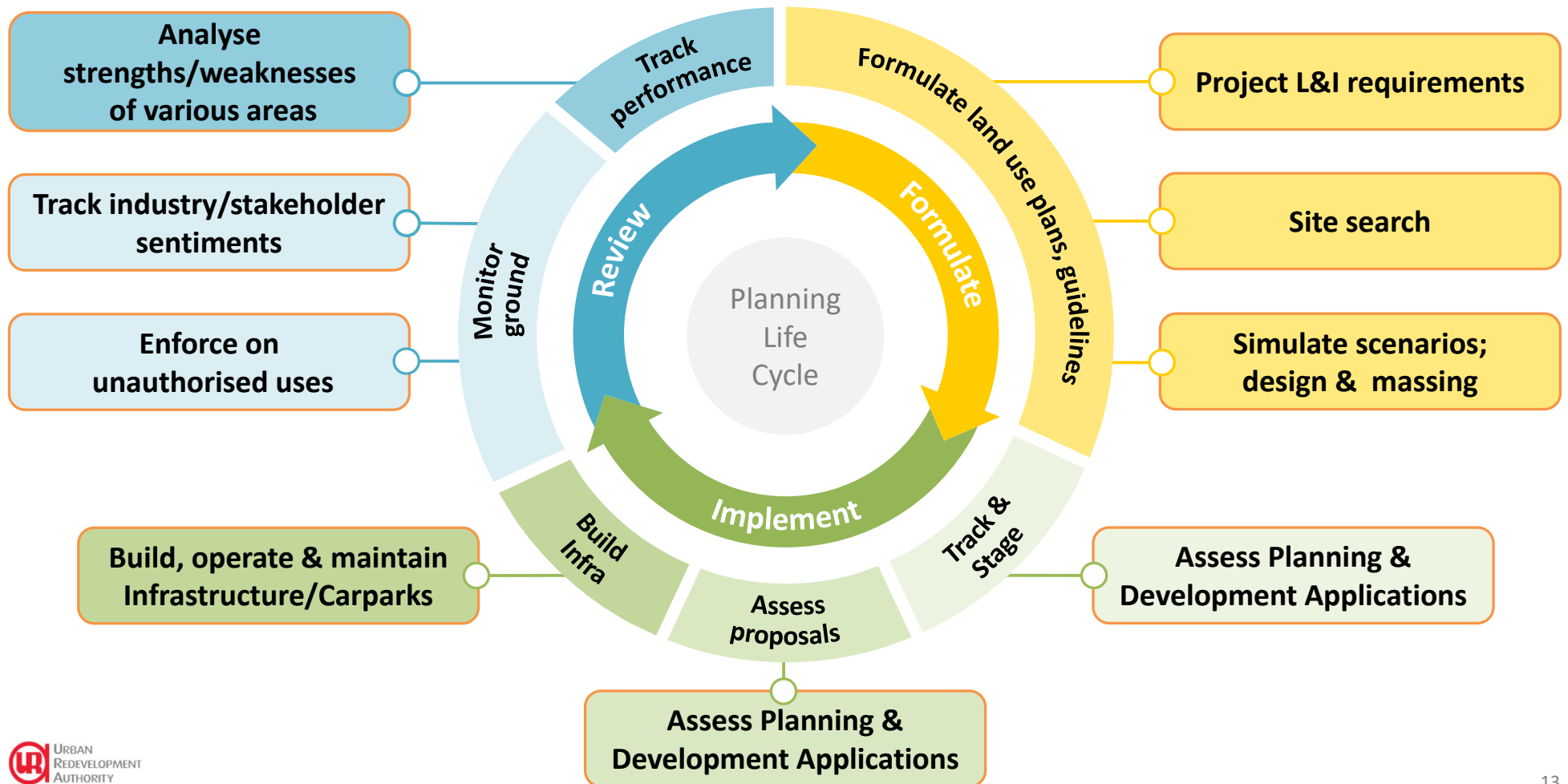
SPECIAL ISSUE

Machine learning advances for time series forecasting

Ricardo P. Masini, Marcelo C. Medeiros ✉ Eduardo F. Mendes

First published: 01 July 2021 | <https://doi.org/10.1111/joes.12429>

URA's "Plan AI" Initiatives



Other Mindsets, Methodologies and Toolsets: Behavioral and Natural Experiments in Policymaking



Recent Nobel Prize in Economics Awards for Experimentation in Policymaking and for Behavioral Economics

2021

<https://www.nobelprize.org/prizes/economic-sciences/2021/summary/>

"... one half awarded to David Card for his empirical contributions to labour economics", the other half jointly to Joshua D. Angrist and Guido W. Imbens "for their methodological contributions to the analysis of causal relationships."

2019

<https://www.nobelprize.org/prizes/economic-sciences/2019/summary/>


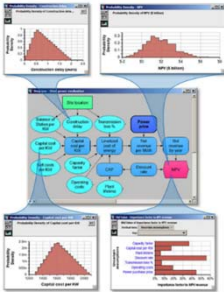

"... jointly to Abhijit Banerjee, Esther Duflo and Michael Kremer "for their experimental approach to alleviating global poverty."

2017

<https://www.nobelprize.org/prizes/economic-sciences/2017/summary/>

"...to Richard H. Thaler "for his contributions to behavioural economics."

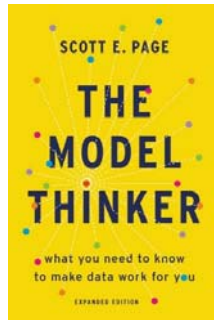
Other Mindsets, Methodologies and Toolsets: Forecasting and Future Scenarios for Policy Analysis

Combining Econometric Based Time Series Forecasting with Machine Learning Methods	Decision Analysis Work – characterizing uncertainty in policy related forecasting (with Sci & Tech uncertainty)	Philip Tetlock's work on Superforecasting
<div data-bbox="113 646 688 885">  <p>SPECIAL ISSUE</p> <p>Machine learning advances for time series forecasting</p> <p>Ricardo P. Masini, Marcelo C. Medeiros, Eduardo F. Mendes</p> <p>First published: 01 July 2021 https://doi.org/10.1111/joes.12429</p> <p>2021</p> </div> <p>Also, using ML in the context of econometric models</p> <div data-bbox="113 1019 688 1279"> <p>Machine Learning: An Applied Econometric Approach</p> <p>Sendhil Mullainathan Jann Spiess</p> <p>JOURNAL OF ECONOMIC PERSPECTIVES VOL. 31, NO. 2, SPRING 2017 (pp. 87-106)</p> <p>2017</p> </div>	<div data-bbox="804 656 1001 950">  <p>2017</p> </div> <div data-bbox="1062 656 1260 950">  <p>1990</p> </div> <div data-bbox="762 984 984 1274">  </div> <div data-bbox="1010 1073 1327 1188">  </div>	<div data-bbox="1589 656 1787 950">  <p>2015</p> </div> <div data-bbox="1425 971 1948 1120">  </div> <div data-bbox="1541 1143 1835 1268">  </div>

The Contributions of Big Data AND Thick Data in Forecasting



Scott Page



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Hybrid Predictive Ensembles: Synergies Between Human and Computational Forecasts

Lu Hong, PJ Lamberson and Scott E Page

- **Big Data** (many attributes, many observations) with AI algorithms outperforms humans for prediction of **“typical cases.”**
- **Thick Data** (more nuanced understandings embedded in narratives) used by humans can better assess and predict **“atypical cases.”**
- **Assessing whether the prediction task involves “typical cases” or “atypical cases.”**



Tricia Wang



May 13, 2013 | 43 Comments

Big Data Needs Thick Data

Using Augmented Intelligence in Responsible Ways by Recognizing Limitations and Strengths

Above and beyond the emerging understanding on the dimensions of responsible AI, e.g.,

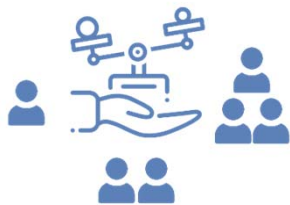


FEAT: Fair, Ethical, Accountable, Transparent or

FAT: Fair, Accountable, Transparent or

FATE: Fair, Accountable, Transparent, Explainable

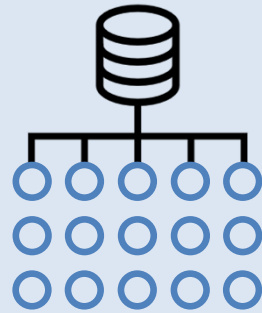
**If we recognize the capabilities AND limitations of machine “intelligence”,
we are much more likely to use AI in responsible ways across the following levels:**



- Individuals
- Teams, units, departments
- Organisations
- Institutions and Sectors (Public, Private, Non-Profit)



Exceeds and Inferior



AI application **Exceeds**
some aspects of human
capability



AI application is **Inferior**
to other aspects of human
capability

Dynamic



Tensions



Exceeds

Inferior



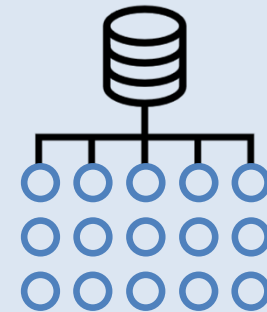


Exceeds and Inferior



- Searching vast amounts of data for relevant information
- Searching vast numbers of alternatives for feasible and optimal choices
- Optimizing over many parameters, possibilities
- Model-based computational simulation, many parameters, complex interactions
- Pattern recognition, especially complex patterns
- Correlations, especially with many dimensions
- **Predictions, classifications**
- **Consistent choices**
- **Optimizing choices, risk minimizing choices**

(Only when the present is same/similar to the past)



AI application **Exceeds**
some aspects of human
capability



Exceeds and Inferior



AI application is **Inferior**
to other aspects of human
capability

- “Common Sense” understanding of the world
- Understanding causality, plausibility
- Understanding context
- Understanding intent, especially when implicit
- Identifying when the “rules of the game” or the nature of the situation has changed
- Intuiting when new questions need to be asked
- Realizing that a “re-framing” is needed
- Bridging from the current environment to a new environment
- Situation assessment and explanations in new circumstances
- Defining standards for “quality”; Defining objectives

From Thomas Davenport & Steven Miller
***Working with AI: Real Stories of Human-Machine Collaboration* forthcoming from MIT Press in 2022**
Chapter on “What Machines Can’t Do (Yet)”

- Understand Context
- Tasks with Subjective Elements
- Prioritizing Alerts in Complex, Dynamic Settings
- Is That Your Final Answer?
- Making Final Disease Diagnoses
- Creating a Coherent Story for Other Humans

- Problem Framing, Training and Coaching
- Multi-Stakeholder Alignment, Negotiation, and Decision-Making
- Understanding Complex, Integrated Entities



- Relationships with Humans
- Providing Job Satisfaction and Nurturing Morale
- Tone Analysis
- Understand Emotional Situations and Needs

- Considering Ethical Implications of AI
- Exercising Discretion About When to Use AI

- Orchestrating Physical Settings for Analysis
- Organizational Change Management

- Create New Knowledge and Transfer it to a System
- Fixing AI Systems

From Kai-Fu Lee and Chen Qiufan
AI 2041: Ten Visions for Our Future, published 2021 by Currency/Penguin Random House
Chapter 8 on “What AI Cannot Do.”



Creativity:

AI cannot create, conceptualize, or plan strategically. While AI is great at optimizing for a narrow objective, it is unable to choose its own goals or to think creatively. Nor can AI think across domains or apply common sense.

Empathy:

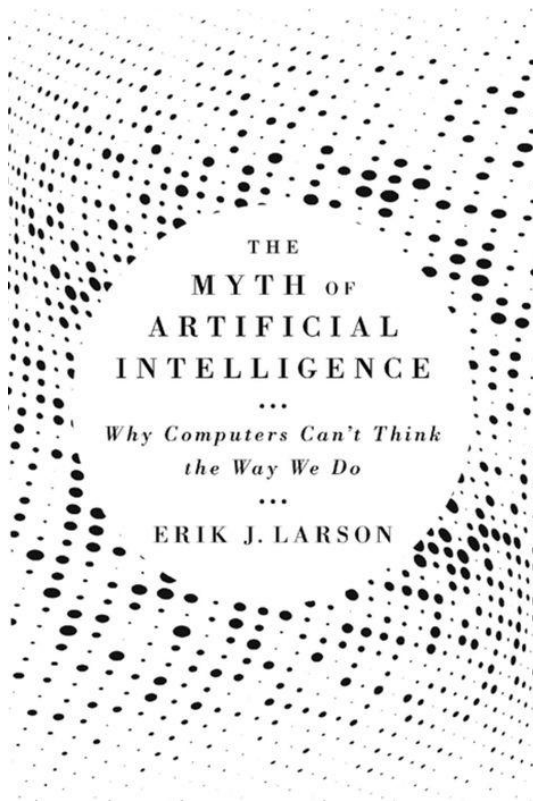
AI cannot feel or interact with feelings like empathy and compassion. Therefore, AI cannot make another person feel understood and cared for. Even if AI improves in this area, it will be extremely difficult to get the technology to a place where humans feel comfortable interacting with robots in situations that call for care and empathy, or what we might call “human-touch services.”

Dexterity:

AI and robotics cannot accomplish complex physical work that requires dexterity or precise hand-eye coordination. AI can’t deal with unknown and unstructured spaces, especially ones that it hasn’t observed.

From Erik Larson

***Artificial Intelligence: Why Computers Can't Think the Way We Do*, published 2021 by Harvard Univ Press
See Part II: The Problem of Inference**



Intelligence requires inference.

There are three types of inference (not two types):

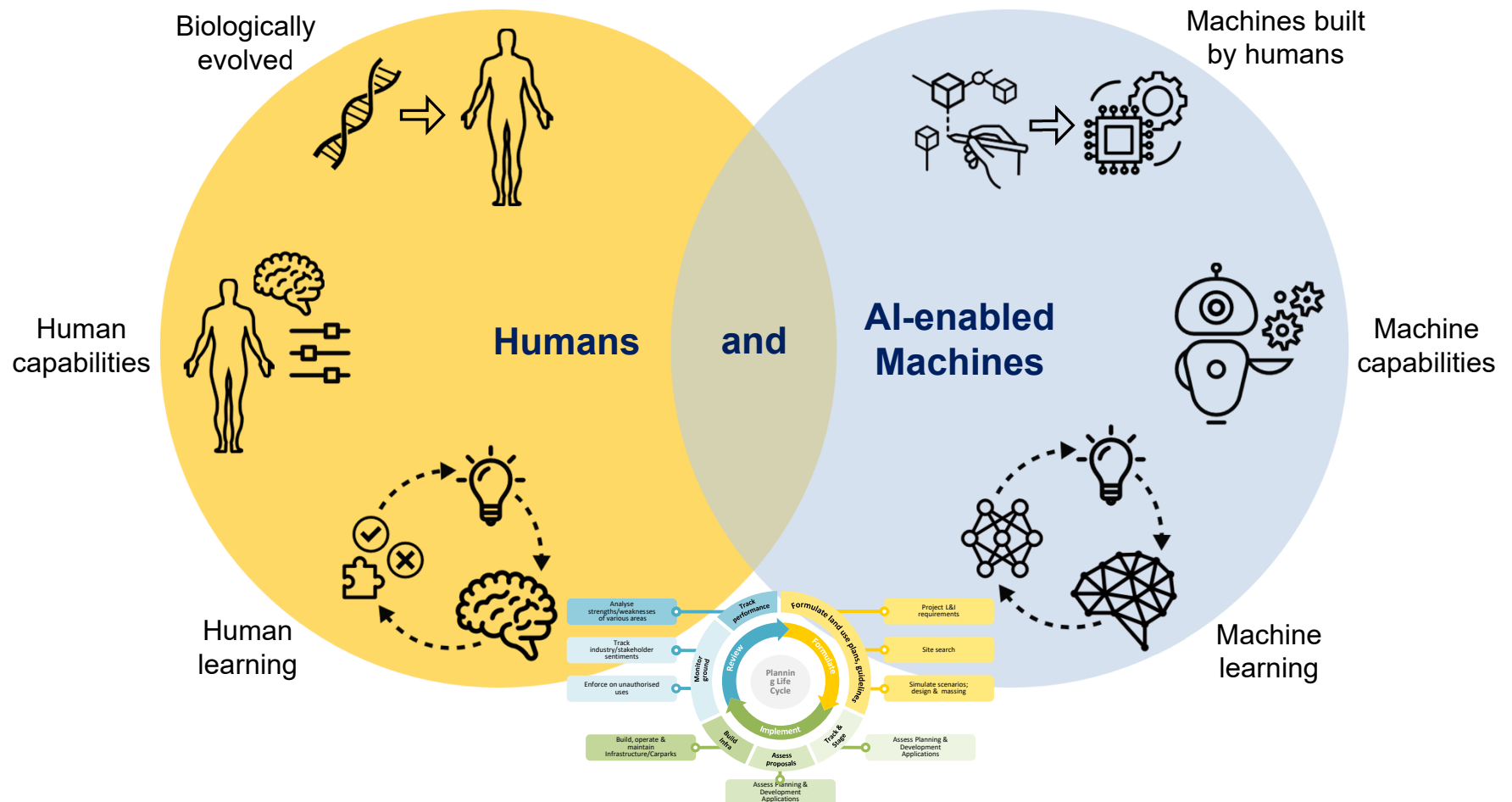
- Deduction (From principles, premises and theories → To inference)
- Induction (From specific examples and data → To inference)
- Abduction (Given results we see, → inferring plausible hypotheses and explanations).

Computational algorithms can do deductive (logic based) inference and inductive (data based) inference very well.

Even so though there are still basic limitations that will not be overcome with larger data sets or bigger computers—especially with inductive inference (e.g., deep neural networks).

**To date, computational algorithms cannot do abduction.
And abduction is an essential aspect of intelligence.**

Combining Human and Machine Intelligence for Urban Planning



Thank You

Special thanks to Nicole Ho for graphics and visualisation
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H HYBRID INTELLIGENCE
ADVISORY