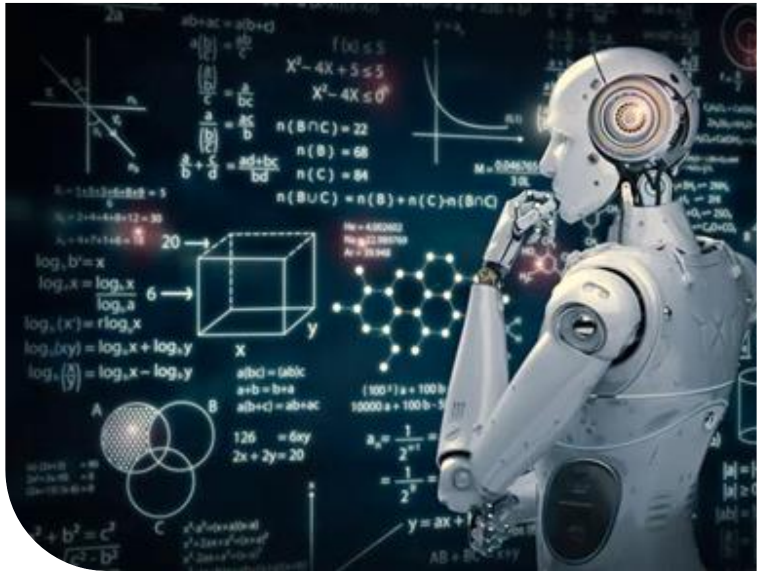
UNIVERSITY OF PASSAU

AI-Based Business Information Systems

AI-Enabled Insights & Decisions



Prof. Dr. Ulrich Gnewuch

Course Organization

Lecture

AI-Enabled Business Capabilities

- AI-Enabled Innovation
- AI-Enabled Insights & Decisions
- AI-Enabled Engagement
- AI-Enabled Automation

AI Technologies & Trends

- AI Ethics & Responsible AI
- Generative AI
- Explainable AI
- Conversational AI

Foundations

- Introduction to AI in Business & Information Systems
- Design & Management of AI-Based Information Systems

Exercise

Exercise 4: Generative AI & Innovation

Exercise 3: Explainable AI Techniques

Exercise 2: Human-Centered Chatbot Design

Exercise 1: Robotic Process Automation Case Study

Industry Talk ZF Group

Information Presentation & Distribution	*How can we present our data (and insights generated from it) to support business decisions?*
Information Generation	*How can we generate useful insights from our data?*
Data Provisioning	*How can we make our data available for analysis?*
Data	*What data do we have? Where does it come from?*

https://www.wiwi.uni-passau.de/en/artificial-intelligence/teaching/courses/business-intelligence-analytics-systems

RECAP FROM LAST LECTURE:

- Please organize the following milestones based on the order in which they happened in the history of conversational AI.
- What are the components of NLP-based conversational AI systems?
- Please provide examples of task-oriented, text-based conversational agents.

Learning Goals

- Describe the concept of AI-enabled insights & decisions and distinguish between its two major paradigms
- Explain the top-down, knowledge-driven paradigm and describe key technologies within this paradigm
- Explain the bottom-up, data-driven paradigm and describe key technologies within this paradigm
- Discuss the last mile of AI-enabled insights & decisions along with its common causes and potential solutions

Costs of Bad Business Decisions

https://www.agencycentral.co.uk/articles/what-is-the-cost-of-making-a-bad-hire/

From $35bn to $7.4bn in nine years

At $35bn (25.83bn), the marriage of Daimler and Chrysler in 1998 was the largest industrial merger in history.

It brought together a German manufacturer whose Mercedes brand was synonymous with high quality, and an American carmaker whose Dodge and Jeep marques had helped it capture a quarter of the US market.

The "merger of equals" was meant to strengthen the pair against more efficient Japanese rivals, protect themselves from market overcapacity, and help them address the environmental concerns that threatened the whole automotive industry.

But nine years on, the experiment has been abandoned. In paying just €5.5bn ($7.4bn) for Chrysler, private equity group Cerberus has shown that the creation of DaimlerChrysler was one of the most unsuccessful mergers of modern times.

Right from the start, there were problems. Although Daimler implemented a rigorous post-merger programme of meetings and seminars in an attempt to bring the two halves of the new company together, former employees have spoken of cultural clashes.

DAIMLER

CHRYSLER

https://www.theguardian.com/business/2007/may/14/motoring.lifeandhealth

Business Value of "Good" Decisions

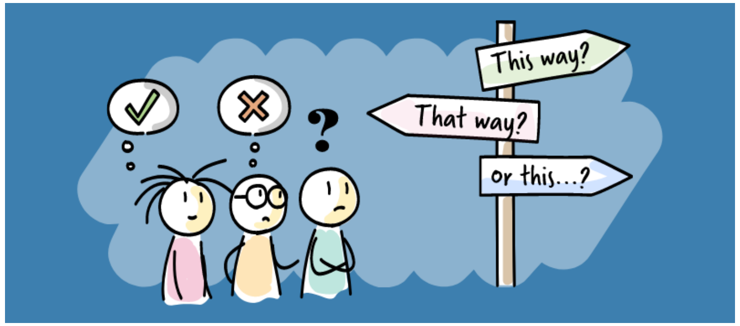
EXAMPLE DECISION	DECISION MAKER	NUMBER OF ANNUAL DECISIONS	ESTIMATED VALUE TO FIRM OF A SINGLE IMPROVED DECISION	ANNUAL VALUE
Allocate support to most valuable customers	Accounts manager	12	$100,000	$1,200,000
Predict call center daily demand	Call center management	4	$150,000	$600,000
Decide parts inventory levels daily	Inventory manager	365	$5,000	$1,825,000
Identify competitive bids from major suppliers	Senior management	1	$2,000,000	$2,000,000
Schedule production to fill orders	Manufacturing manager	150	$10,000	$1,500,000
Allocate labor to complete a job	Production floor manager	100	$4,000	$400,000

Laudon & Laudon 2022

Decision-Making

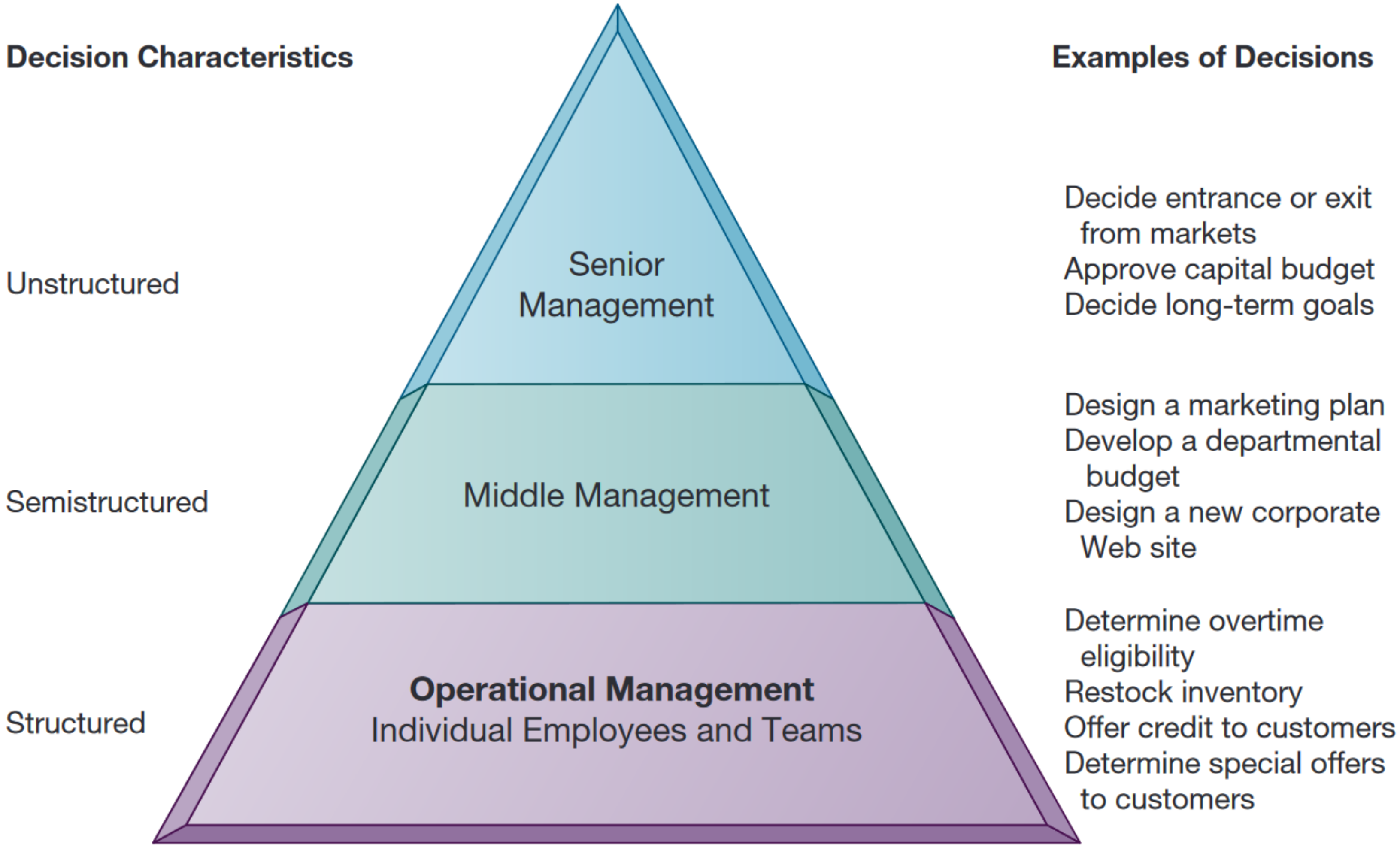
Decision-making is the process of sufficiently reducing uncertainty and doubt about alternatives to allow a reasonable choice to be made from among them.

- Reducing uncertainty by gathering information about all alternatives is crucial
- Uncertainty can only be reduced, not eliminated
- Very few decisions are made with absolute certainty because complete knowledge about all the alternatives is seldom possible!



Harris 1998

Decision-Making at Different Levels



Strategic Decisions

Tactical Decisions

Operational Decisions

Laudon & Laudon 2022

“Gut Decisions”

How to Make More Informed Decisions?

Ask an expert

Discuss alternatives
with peers

Use data and technology (e.g., AI)

AI-Enabled Insights & Decisions

AI-enabled insights and decisions refers to the use of AI to provide meaningful insights and inform decision-making processes.

- A wide range of different AI technologies has been used for this purpose, including:
  - Expert / Knowledge-based systems
  - Machine learning applications
  - …

What is the patient's medical problem?

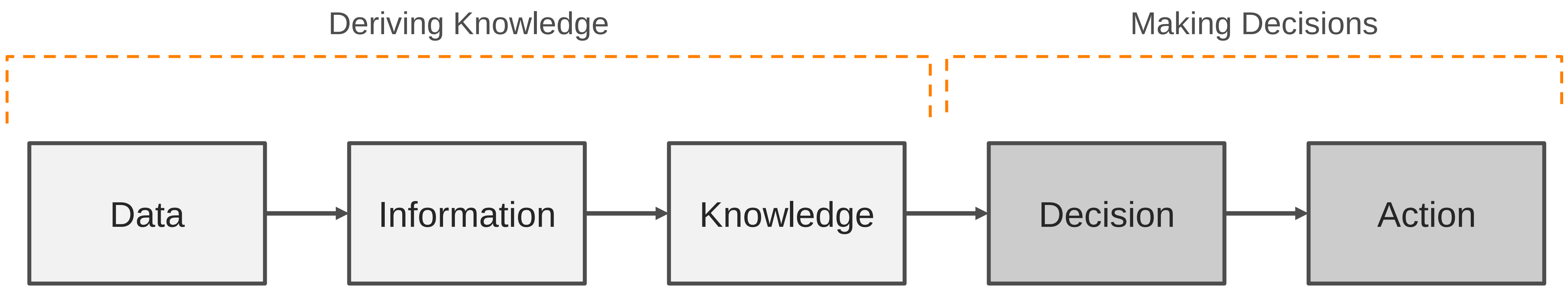
Which product should I buy?

When will this machine probably fail?

Which groups of customers does our business currently serve?

Benbya et al. 2021

Information Value Chain: From Insights to Decisions



- Good decisions require knowledge and information (“insights”), both of which can be derived from data (manually through experience or automatically using technology)
- Ideally, these decisions lead to effective actions

Abbasi et al. 2016

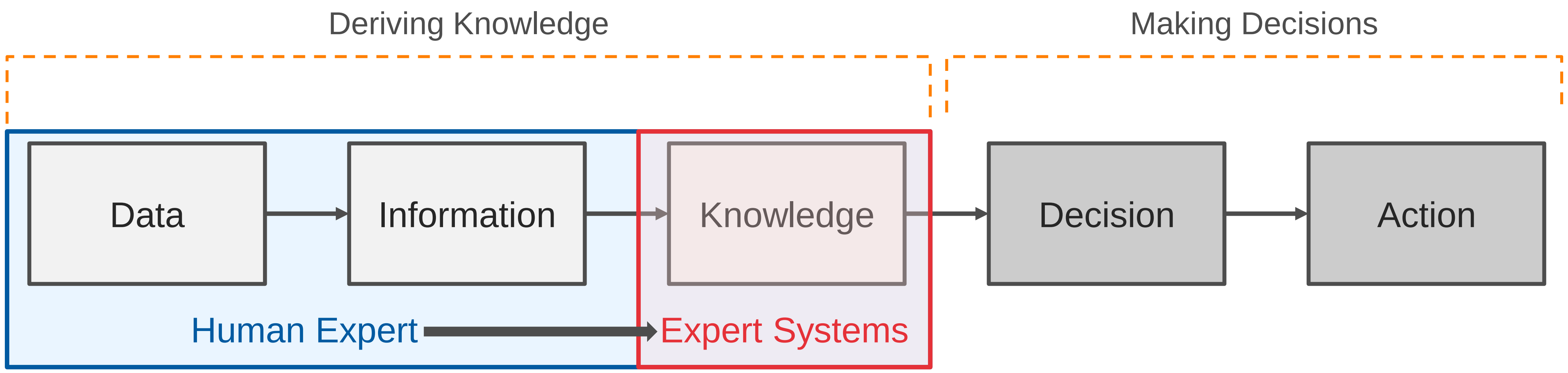
Two Paradigms of AI-Enabled Insights & Decisions

Providing insights and informing decisions

Russel & Norvig 2016

Top-Down
Knowledge-Driven Paradigm

Top-Down, Knowledge-Driven Paradigm



- Human experts have used their intelligence to develop a high level of expertise in a particular domain by training, education, and learning from experience
- The top-down, knowledge-driven paradigm seeks to “transfer” as much of this expert knowledge as possible to machines
- Consequently, these systems are often called “expert systems”

Abbasi et al. 2016; Russel & Norvig 2016

Expert Systems

Expert systems are computer programs designed to assist in decision-making by reasoning through knowledge captured from human experts within a specific domain.

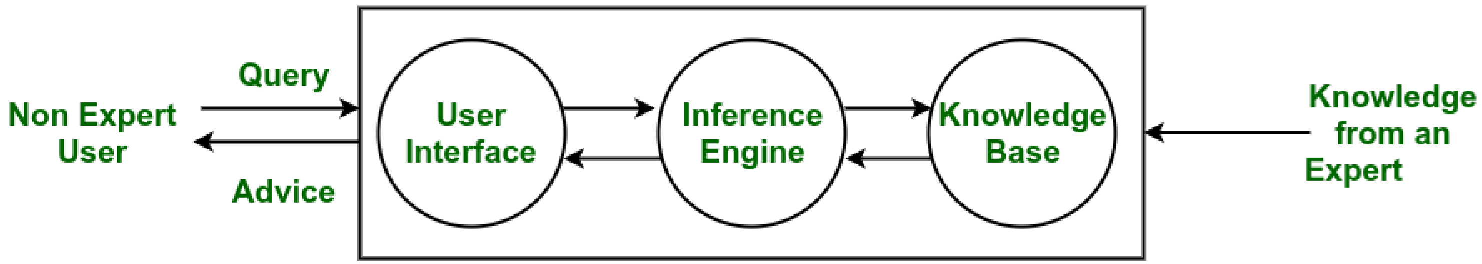
- Their main goal is to simulate the decision-making skills of human experts in very specific domains by using hard-coded rules (e.g., “if-then” statements) and logical inference techniques

- Expert systems emerged in the 1970s as a breakthrough in AI research
- They were the dominant AI technology in the 1980s but disappeared in the 1990s → Today, they are often not considered AI anymore

- The term “expert system” was used interchangeably with “knowledge-based system”

El-Najdawi & Stylianou 1993

Expert System Architecture



- Expert systems have three main components:
  1. A **knowledge base** consisting of knowledge captured from an expert in the domain, encoded into facts, rules, and relationships
  2. An **inference engine** that processes information from the knowledge base, applies logical reasoning techniques, and generates recommendations
  3. A **user interface** that allows non-experts to interact with and receive advice or recommendations from the system

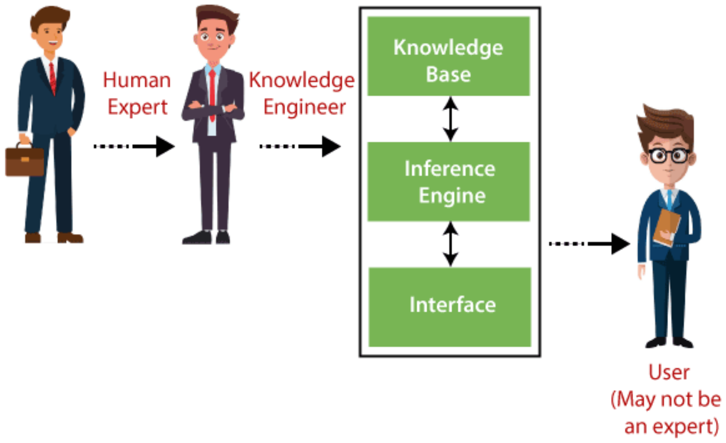
- Sometimes, an “explanation facility” component was included to help users understand the reasoning process of the system

El-Najdawi & Stylianou 1993

Expert System Development

- Developing an expert system is known as *knowledge engineering,* and its practitioners are called *knowledge engineers*

- Knowledge engineers typically follow this process:
  1. Interviewing and observing human experts
  2. Learning what the experts know and how they reason with their knowledge
  3. Translating this knowledge into a set of rules
  4. Loading these rules into an inference engine and running them against test cases
  5. Consulting with human experts to determine what changes need to be made



Haigh 2024

Example #1: MYCIN

- One of the best-known expert systems is MYCIN (developed in the 1970s)
- It was designed to provide advice for physicians regarding diagnosis and therapy for infectious diseases
- MYCIN’s medical knowledge was encoded in a set of rules that represent a single, independent “chunk” of domain-specific knowledge
- A consultation was run by backward chaining through applicable rules

```
PREMISE: (AND (SAME CNTXT INFECT PRIMARY-BACTEREMIA)
              (MEMBF CNTXT SITE STERILESITES)
              (SAME CNTXT PORTAL GI))
ACTION: (CONCLUDE CNTXT IDENTITY BACTEROIDES TALLY .7)

IF: 1) The infection is primary-bacteremia, and
    2) the site of the culture is one of the sterile sites, and
    3) the suspected portal of entry of the organism is the
       gastro-intestinal tract,
THEN: There is suggestive evidence (.7) that identity of the
       organism is bacteroides.
```

Example MYCIN Rule

Davis et al. 1977; Moore & Swartout 1988

Example #2: R1

- The first successful commercial expert system was R1
- Developed by John McDermott of Carnegie Mellon University and used by Digital Equipment Corporation (DEC; later bought by HP)
- R1 helped configure orders for new computer systems based on 2500 rules
- By 1986, it had processed 80,000 orders and was saving DEC an estimated $40 million a year
- By 1988, DEC had 40 expert systems deployed
- McDermott’s 1982 paper on R1 won the AAAI Classic Paper Award in 1999

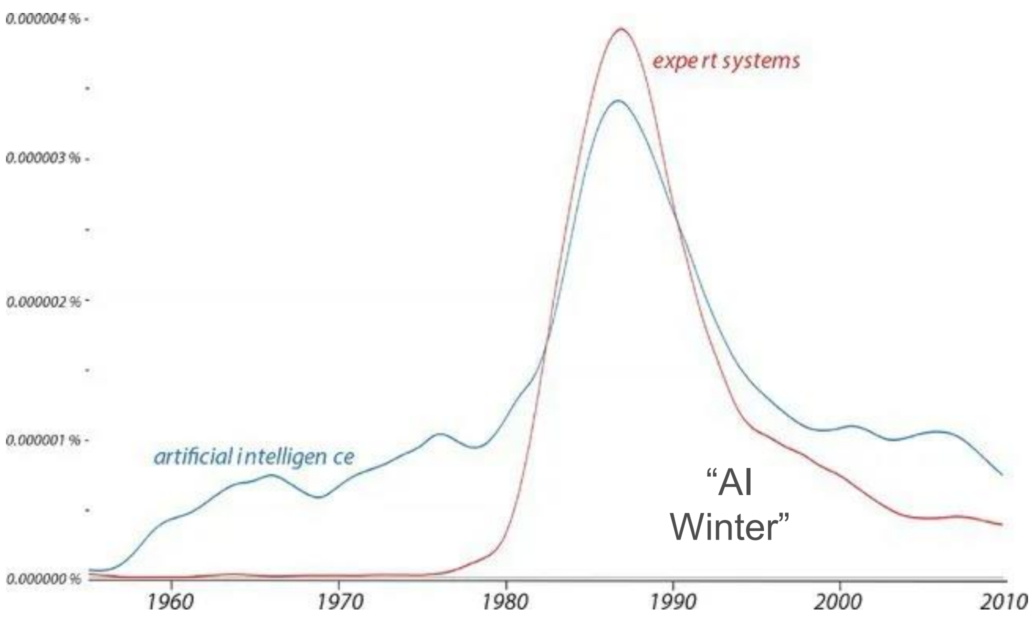
```
ASSIGN-UB-MODULES-EXCEPT-THOSE-CONNECTING-TO-PANELS-4

   IF:  THE CURRENT CONTEXT IS ASSIGNING DEVICES
            TO UNIBUS MODULES
        AND THERE IS AN UNASSIGNED DUAL PORT DISK DRIVE
        AND THE TYPE OF CONTROLLER IT REQUIRES IS KNOWN
        AND THERE ARE TWO SUCH CONTROLLERS NEITHER
            OF WHICH HAS ANY DEVICES ASSIGNED TO IT
        AND THE NUMBER OF DEVICES THAT THESE
            CONTROLLERS CAN SUPPORT IS KNOWN

 THEN:  ASSIGN THE DISK DRIVE TO EACH OF THE CONTROLLERS
        AND NOTE THAT THE TWO CONTROLLERS HAVE BEEN
            ASSOCIATED AND THAT EACH SUPPORTS ONE DEVICE
```

Example R1 Rule

McDermott 1982; Russel & Norvig 2016

Rise and Fall of Expert Systems

- The development of expert systems marked a turning point in the history of AI
- They served as proof that AI systems could be used in real-life systems and had the potential to provide significant benefits to businesses
- Expert systems generated a lot of hype, and the AI industry boomed from a few million dollars in 1980 to billions of dollars in 1988:
  - *“Expert system startups were mushrooming, large corporations were rushing to establish AI groups, government money was flooding in, and a frenzied job market ensured lucrative employment for anyone who could claim a few months of AI experience”*
- However, expert systems failed to deliver on their overhyped promises, resulting in a significant slowdown of business interest and investments



Google’s Ngram chart showing the explosion of discourse around expert systems in the 1980s

Haigh 2024

The Rise and Fall of Expert Systems

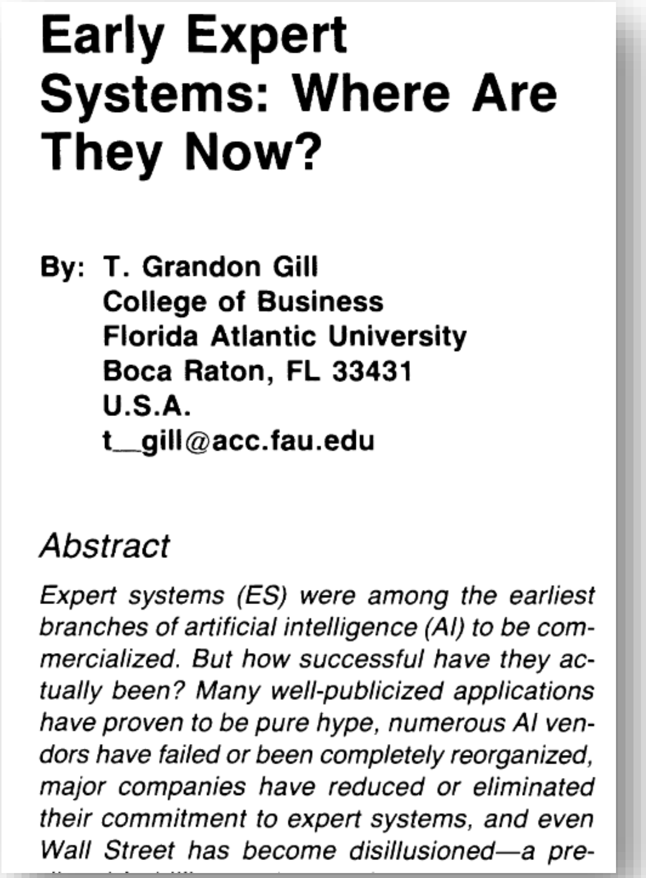
What caused the fall of expert systems? Why did they fail and what challenges couldn’t they overcome? What do you think?

Mentimeter

Limitations and Challenges of Expert Systems

- While expert systems did well in narrow problem domains, they struggled when faced with a situation outside their knowledge base:
  - They could not learn new knowledge on their own (e.g., generate new rules) and were reliant on human experts and programmers to make adjustments
  - Keeping them up to date was time-consuming (→ costs) and difficult (→ skilled knowledge engineers)

- Complex tasks often require <u>tacit</u> knowledge that experts find hard to codify
- Decision-makers (e.g., doctors) were reluctant to trust computer-generated advice (e.g., a diagnosis) over their gut instinct



Early Expert Systems: Where Are They Now?

By: T. Grandon Gill
College of Business
Florida Atlantic University
Boca Raton, FL 33431
U.S.A.
t_gill@acc.fau.edu

Abstract

Expert systems (ES) were among the earliest branches of artificial intelligence (AI) to be commercialized. But how successful have they actually been? Many well-publicized applications have proven to be pure hype, numerous AI vendors have failed or been completely reorganized, major companies have reduced or eliminated their commitment to expert systems, and even Wall Street has become disillusioned—a pre-

Gill 1995, Haigh 2024

Expert Systems are Not Dead

Die Bundesregierung

Nationale Strategie für Künstliche Intelligenz

AI Made in Germany

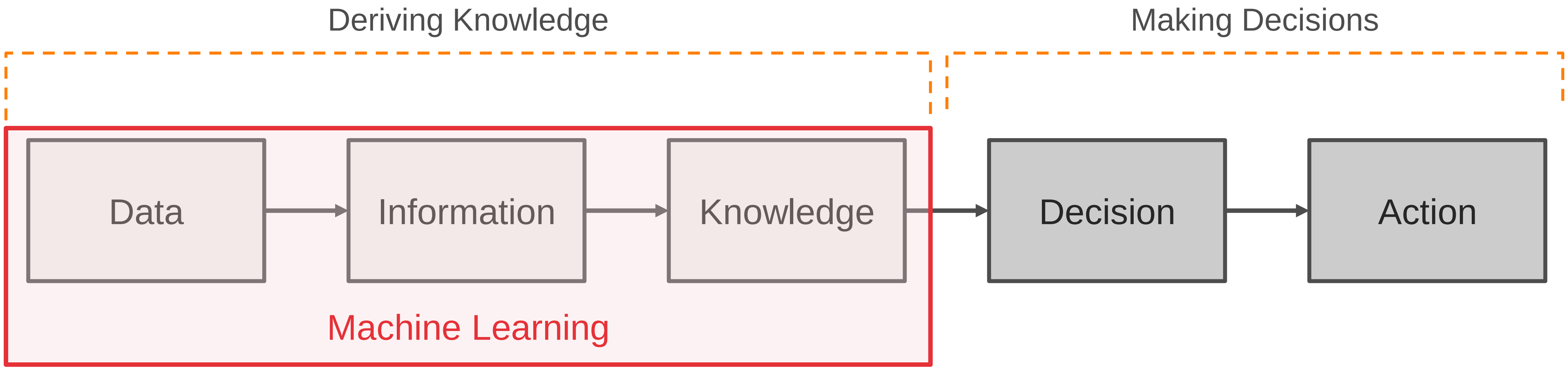
Die Bundesregierung orientiert sich bei ihrer Strategie an der Nutzung der KI für die Lösung von Anwendungsproblemen und damit an den Positionen der „schwachen“ KI:

1. Deduktionssysteme, maschinelles Beweisen: Ableitung (Deduktion) formaler Aussagen aus logischen Ausdrücken, Systeme zum Beweis der Korrektheit von Hardware und Software;
2. Wissensbasierte Systeme: Methoden zur Modellierung und Erhebung von Wissen; Software zur Simulation menschlichen Expertenwissens und Unterstützung von Experten (ehemals: „Expertensysteme“); zum Teil auch verbunden mit Psychologie und Kognitionswissenschaften;
3. Musteranalyse und Mustererkennung: induktive Analyseverfahren allgemein, insbesondere auch maschinelles Lernen;
4. Robotik: autonome Steuerung von Robotik-Systemen, d.h. autonome Systeme;
5. Intelligente multimodale Mensch-Maschine-Interaktion: Analyse und „Verstehen“ von Sprache (in Verbindung mit Linguistik), Bildern, Gestik und anderen Formen menschlicher Interaktion.

https://www.ki-strategie-deutschland.de

Bottom-Up
Data-Driven Paradigm

Bottom-Up, Data-Driven Paradigm



- In the 1990s, there is a shift from a knowledge-driven paradigm to a data-driven paradigm
- In the bottom-up data-driven paradigm, algorithms discover patterns and learn their own rules from data ("training data")
- Their "machine knowledge" is acquired without relying on input or instruction from human domain experts

Abbasi et al. 2016; Russel & Norvig 2016

Machine Learning

Machine learning is a subfield of artificial intelligence that uses algorithms trained on data sets to create models that enable machines to perform tasks without explicit instructions.

- The field of machine learning has been inspired by the idea that humans learn through experience (e.g., by examples or by interacting with the environment)
- Machine learning algorithms iteratively learn from problem-specific training data, which allows them to find hidden insights and recognize complex patterns
  - Range from very simple (e.g., linear regression) to highly complex (e.g., neural networks)
- In the 2010s, deep learning became feasible, which led to machine learning becoming the mainstream AI technology

Note: Technical details are not covered in this lecture.

Janiesch et al. 2021

Overview of Machine Learning (ML) Algorithms

Machine Learning

Supervised Learning

Algorithms learn from **labeled** data

Examples: Predictive maintenance, fraud detection

Unsupervised Learning

Algorithms learn from **unlabeled** data

Examples: Customer segmentation; anomaly detection

Reinforcement Learning

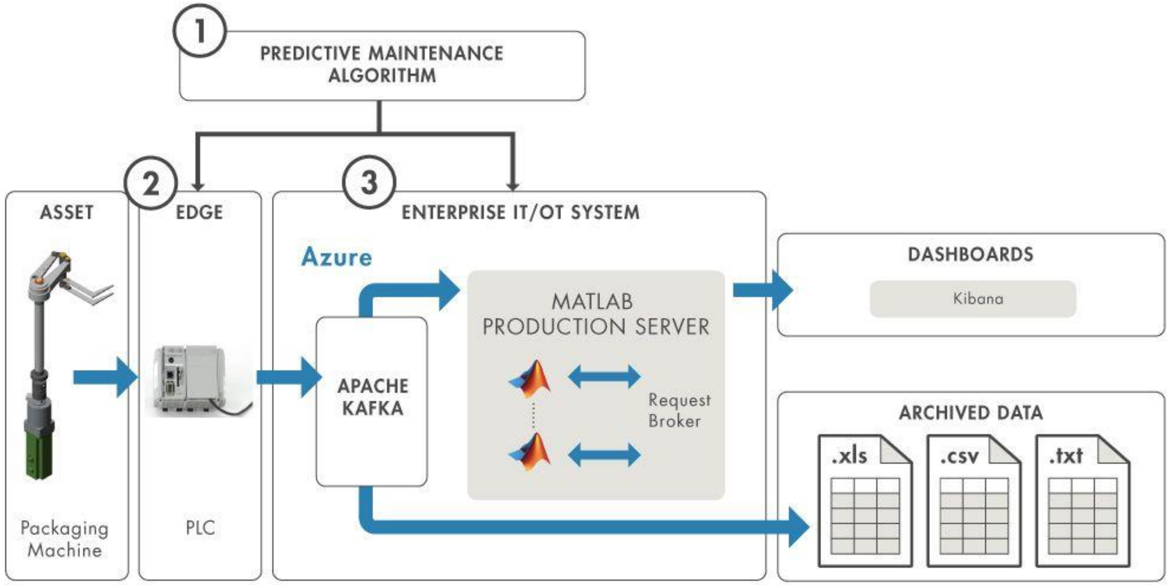
Algorithms (“**agents**”) learn to make decisions by **interacting with an environment** and receiving feedback through **rewards** or penalties

Examples: Automated stock trading, autonomous cars

Janiesch et al. 2021

Example #1: Predictive Maintenance

- The goal of predictive maintenance is to catch breakdowns before they happen by monitoring equipment conditions
  - Typically relies on sensor data enabled by Internet-of-Things (IoT) technology
- When historical data from machine operations is available, **supervised learning** techniques can be employed to predict when a failure will occur and to estimate the machine's remaining useful life
- Predictive maintenance allows maintenance measures to be organized more efficiently and downtimes to be almost completely avoided



Example: Predictive Maintenance System using MATLAB

https://www.mathworks.com/company/technical-articles/deploying-predictive-maintenance-algorithms-to-the-cloud-and-edge.html

Example #2: Customer Segmentation

- Customer segmentation is the process of dividing a customer base into distinct groups of individuals that have similar characteristics, needs, or behaviors
- It is one of **unsupervised learning**'s most important applications
- Enables companies to tailor communications and offerings for each customer segment

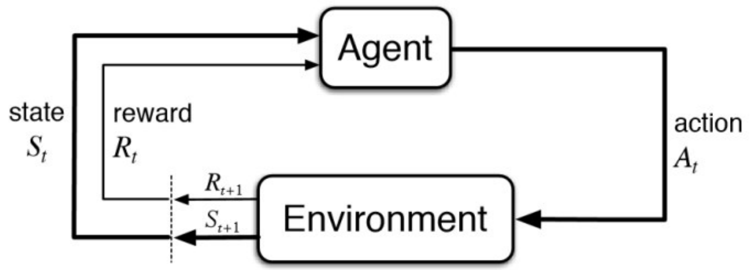
Customer Segment	Description
First-Time Homebuyers	Individuals or couples looking to purchase their first home.
Retirees	Older adults looking to downsize or find homes that fit their lifestyle, with a focus on comfort and accessibility.
Investors	Individuals or entities looking to purchase properties for rental income or long-term capital appreciation.
...	…

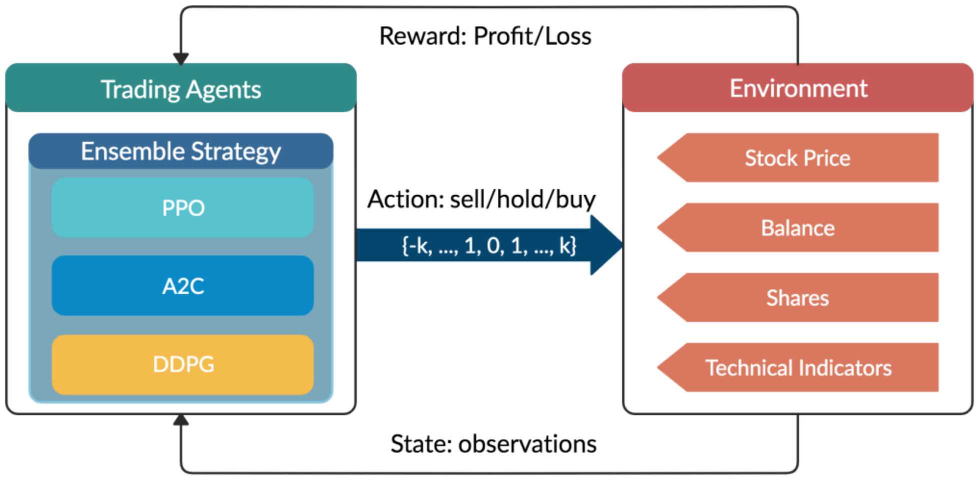
Example: Real Estate Customers

Sharda et al. 2014

Example #3: Automated Stock Trading

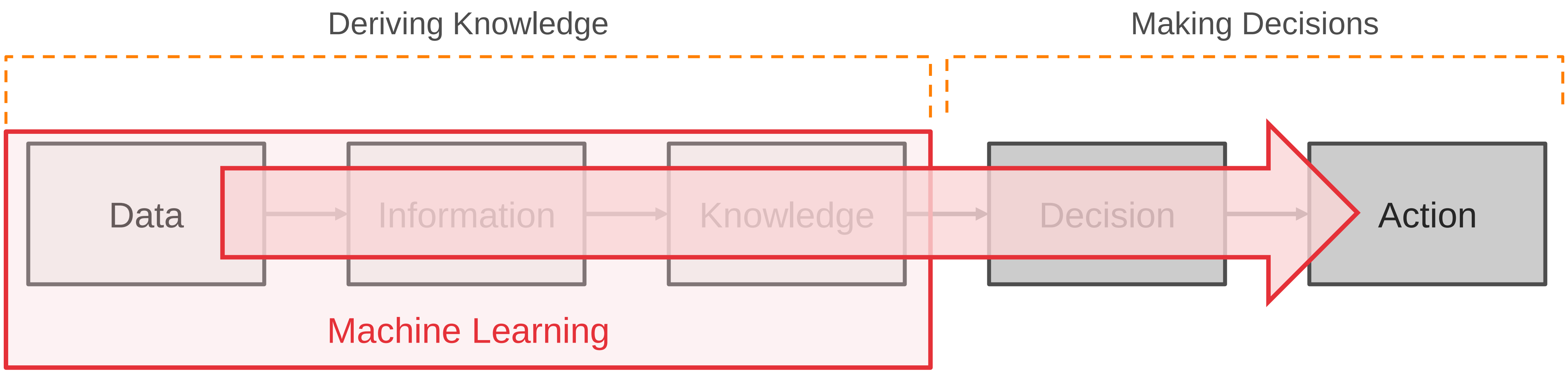
- Stock trading strategies play a critical role in investment, but it is challenging to design a profitable strategy in a complex and dynamic stock market
- Deep **reinforcement learning** (RL) algorithms can be used to find the optimal trading strategy
- Unlike traditional machine learning approaches, RL algorithms learn from trial and error, adapting and optimizing strategies based on past experiences and market feedback





Yang et al. 2020

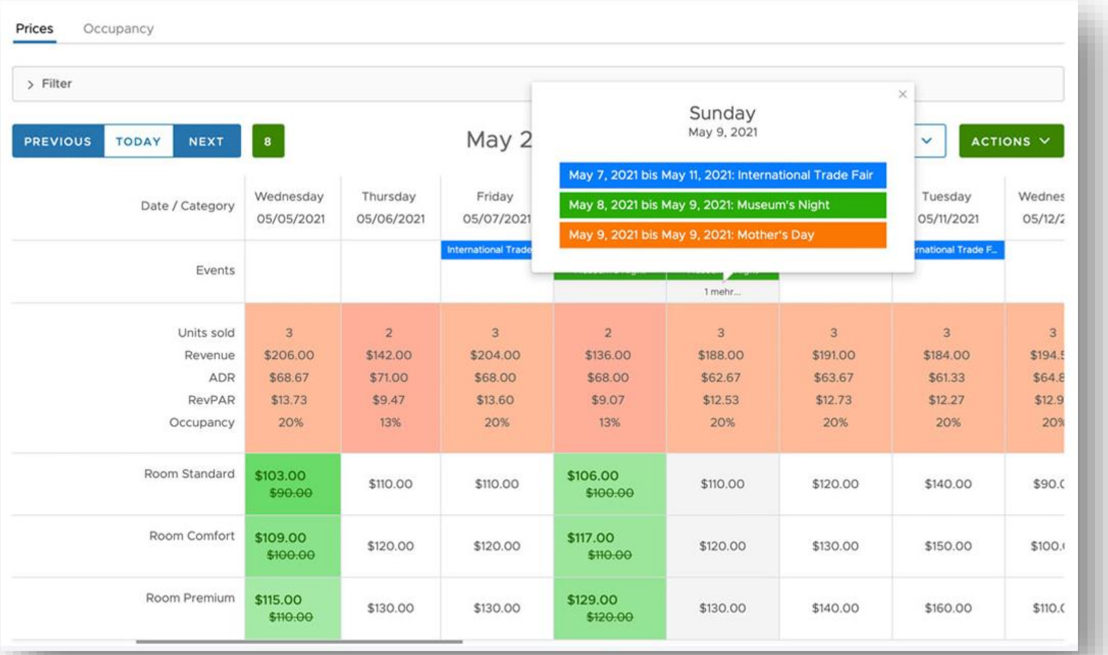
Automated Decision-Making



- Instead of presenting recommendations and insights to a human decision-maker, an AI system may also **autonomously make decisions**
- This approach can streamline decision-making processes but is not always feasible or ethically appropriate in all situations

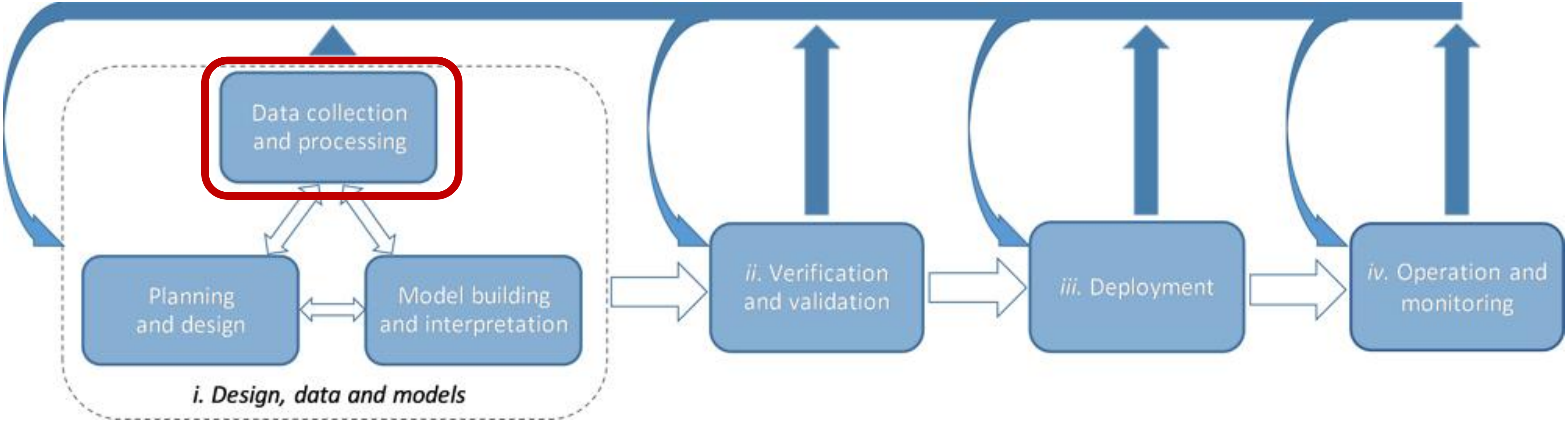
Example: Dynamic Pricing

- Dynamic pricing is a pricing strategy that uses variable prices instead of fixed prices
  - Norm for airline tickets, hotel rooms, and ride-sharing services
- Prices are determined **without human involvement** based on various factors, such as real-time customer demand, season, supply changes, etc.
- Dynamic pricing allows companies to offer prices that are attractive to customers while maximizing profit



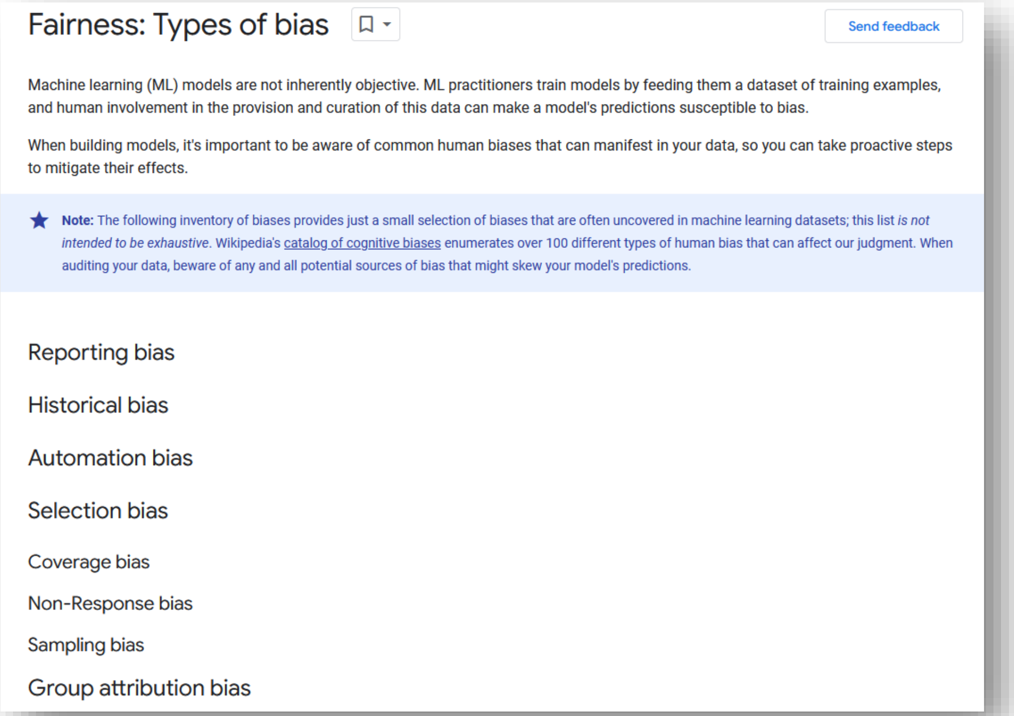
Example: https://happyhotel.uk/dynamic-pricing/

Challenges of the Data-Driven Paradigm



OECD's AI Systems Lifecycle (2019)

Data Collection and Processing: Bias


Fairness: Types of bias

Send feedback

Machine learning (ML) models are not inherently objective. ML practitioners train models by feeding them a dataset of training examples, and human involvement in the provision and curation of this data can make a model's predictions susceptible to bias.

When building models, it's important to be aware of common human biases that can manifest in your data, so you can take proactive steps to mitigate their effects.

★ **Note:** The following inventory of biases provides just a small selection of biases that are often uncovered in machine learning datasets; this list *is not intended to be exhaustive*. Wikipedia's catalog of cognitive biases enumerates over 100 different types of human bias that can affect our judgment. When auditing your data, beware of any and all potential sources of bias that might skew your model's predictions.

Reporting bias

Historical bias

Automation bias

Selection bias

Coverage bias

Non-Response bias

Sampling bias

Group attribution bias

https://developers.google.com/machine-learning/crash-course/fairness/types-of-bias


Insight - Amazon scraps secret AI recruiting tool that showed bias against women

By **Jeffrey Dastin**

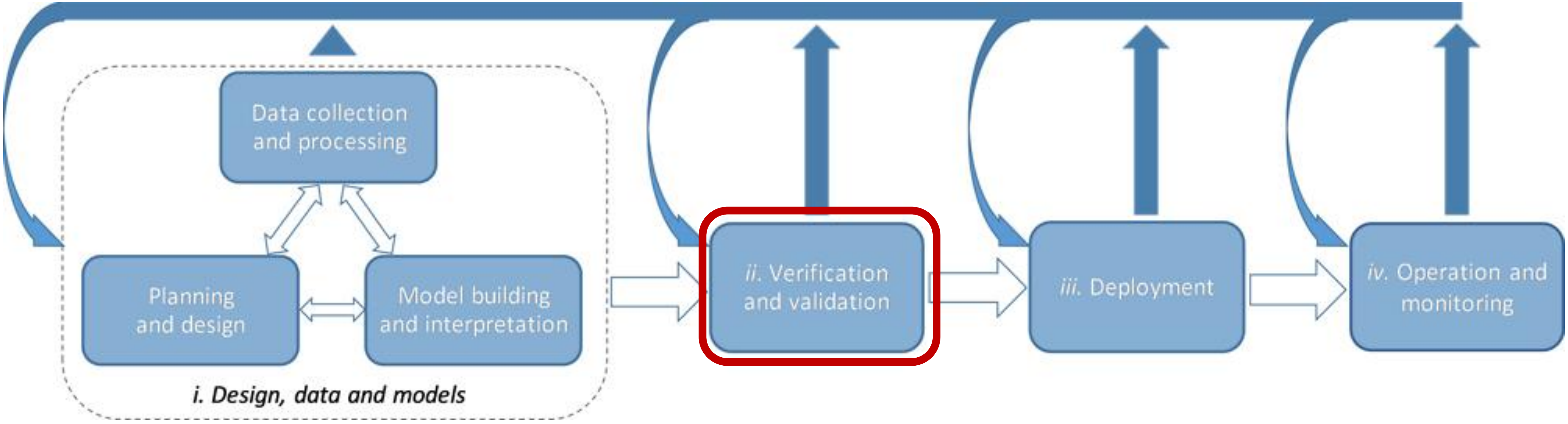
October 11, 2018 2:50 AM GMT+2 · Updated 6 years ago

Aa

SAN FRANCISCO (Reuters) - Amazon.com Inc's machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.

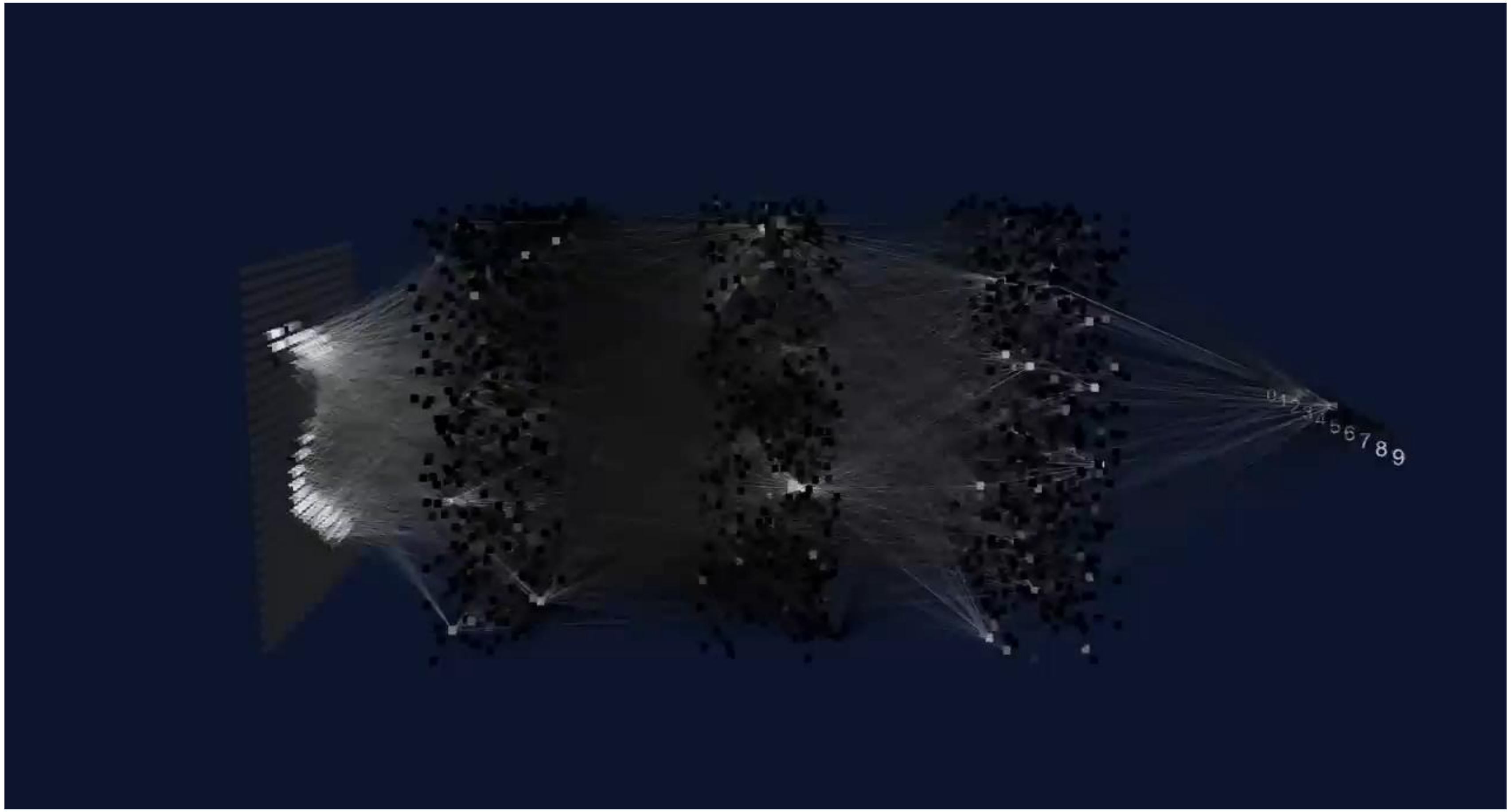
https://www.reuters.com/article/world/insight-amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK0AG/

Challenges of the Data-Driven Paradigm



OECD's AI Systems Lifecycle (2019)

Verification and Validation: Black-Box Problems



https://www.youtube.com/watch?v=Tsvxx-GGlTg

Neural network for recognizing handwritten digits (MNIST dataset)

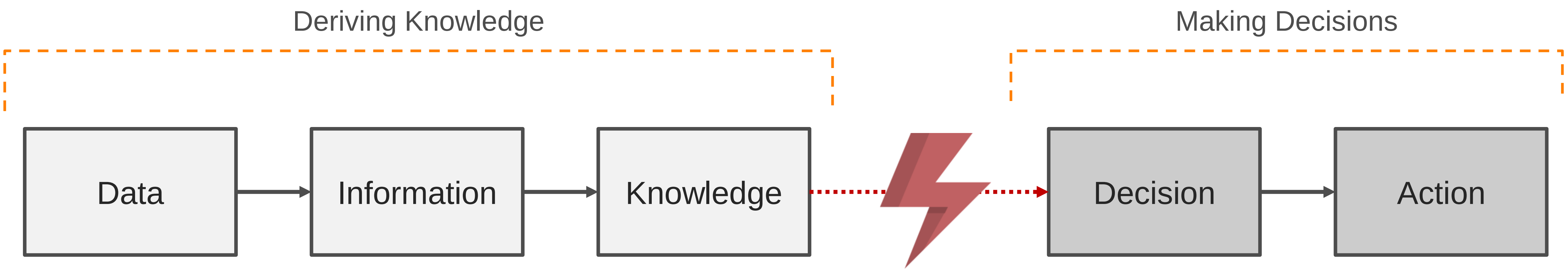
→ Explainable AI Lecture

The Last Mile of AI-Enabled Insights & Decisions

The Last Mile

https://www.youtube.com/watch?v=8WKfCuhdXo4

The Last Mile = Gap Between Knowledge and Decision



- Decision-makers often still rely on their instincts or “gut feelings” instead of leveraging AI-enabled insights and recommendations
- This tendency persists regardless of the AI technology in use (e.g., expert systems, ML applications)

Abbasi et al. 2016

The Last Mile of AI-Enabled Insights & Decisions

Decision-makers often still rely on their instincts or "gut feelings" instead of leveraging AI-enabled insights and recommendations. This tendency persists regardless of the AI technology in use.

Why would employees not consider AI-enabled insights and recommendations in their decision-making? How would you address this problem?

→ Discuss this question with a partner for **~5 minutes** and be ready to share your thoughts

Organizational Decision-Making Culture

- *Data-driven* culture refers to the extent to which it is the norm to use data and analysis to inform decision-making

- To benefit from AI, decisions must be based on “the facts,” and there should be constant experimentation to see what works best
- **Changing the organizational culture associated with how decisions are made can be more challenging than solving technical issues!**

Big Companies Are Embracing Analytics, But Most Still Don’t Have a Data-Driven Culture

by Thomas H. Davenport and Randy Bean

For six consecutive years NewVantage Partners has conducted an annual survey on how executives in large corporations view data. Each year the response rate increases, and the reported urgency of making effective use of data increases as well. This year the results are both more encouraging and more worrisome than in the past.

https://hbr.org/2018/02/big-companies-are-embracing-analytics-but-most-still-dont-have-a-data-driven-culture

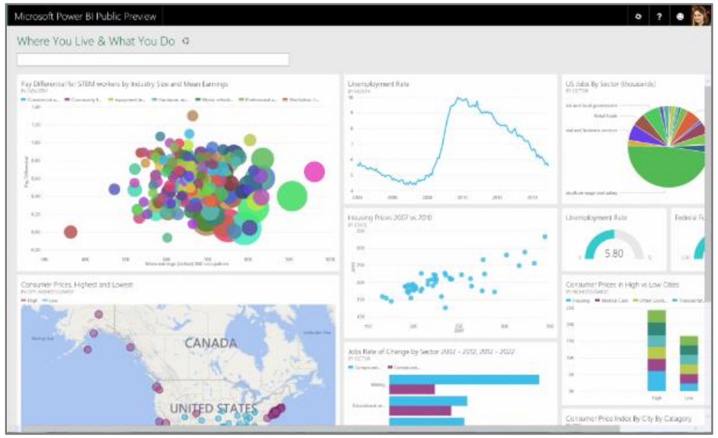
Trieu et al. 2022

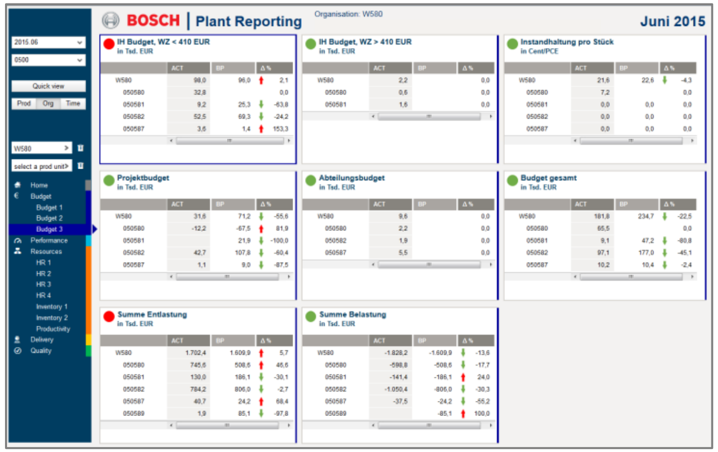
One Way to Bridge the Last Mile: Dashboards

UNIVERSITY OF PASSAU

BOSCH

- Dashboards can be used to democratize access to AI-enabled insights and support decision-making at all levels of an organization
- With intuitive, real-time data visualizations and self-service analytics capabilities, decision-makers can better understand how insights and recommendations were derived
- This transparency not only enhances trust and confidence in AI but also promotes a culture of data-driven decision-making

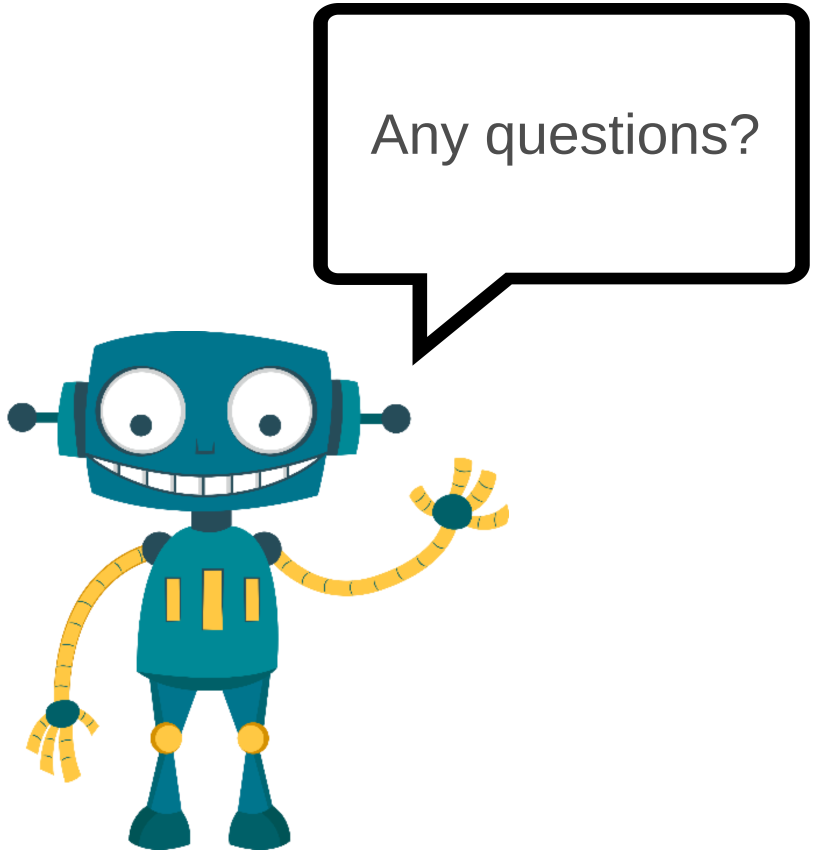




Key Takeaways From This Lecture

- Decision-making is vital to the success of any business but can often be challenging → AI can be used to provide insights and support decision-making
- There are two paradigms of AI-enabled insights & decisions: knowledge-driven (top-down) and data-driven (bottom-up)
- The knowledge-driven paradigm focuses on encoded human knowledge and rule-based logic (e.g., handcrafted rules)
  - Expert systems based on this paradigm gained popularity in the 1980s but eventually disappeared due to significant challenges (e.g., high maintenance costs, inability to capture tacit knowledge)
- In contrast, the data-driven paradigm allows algorithms to discover and learn knowledge directly from large datasets
  - Machine learning, the dominant technology in this paradigm, has become the cornerstone of modern AI
- Despite advancements in AI, decision-makers often still rely on their instincts rather than on AI-enabled insights and recommendations → Changes to an organization's decision-making culture are needed

Thank you for your attention!



References

Abbasi, A., Sarker, S., & Chiang, R. (2016). Big Data Research in Information Systems: Toward an Inclusive Research Agenda. Journal of the Association for Information Systems, 17(2), I–XXXII.

Benbya, H., Pachidi, S., & Jarvenpaa, S. L. (2021). Special Issue Editorial : Artificial Intelligence in Organizations : Implications for Information Systems Research. Journal of the Association for Information Systems, 22, 281–303.

Davis, R., Buchanan, B., & Shortliffe, E. (1977). Production rules as a representation for a knowledge-based consultation program. Artificial intelligence, 8(1), 15-45.

El-Najdawi, M. K., & Stylianou, A. C. (1993). Expert support systems: integrating AI technologies. Communications of the ACM, 36(12), 55-ff.

Gill, T. G. (1995). Early expert systems: Where are they now? MIS Quarterly, 19(1), 51-51.

Haigh, T. (2024). How the AI Boom Went Bust. Communications of the ACM, 67(2), 22-26.

Harris, R. (1998) Introduction to Decision Making. Virtual Salt. http://www.virtualsalt.com/crebook5.htm

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. Electronic Markets, 31(3), 685–695.

Laudon, K. C., & Laudon, J. P. (2022). Management information systems: Managing the digital firm. 17th Edition. Pearson.

McDermott, J. (1982). R1: A rule-based configurer of computer systems. Artificial intelligence, 19(1), 39-88.

Moore, J. D., & Swartout, W. R. (1988). Explanation in expert systems: A survey (No. 228). Marina del Rey, CA, USA: University of Southern California, Information Sciences Institute.

OECD (2019), Artificial Intelligence in Society, OECD Publishing, Paris, https://doi.org/10.1787/eedfee77-en

Russell, S. J., & Norvig, P. (2012). Artificial Intelligence: A Modern Approach. London.

Sharda, R., Delen, D., & Turban, E. (2014). Business intelligence and analytics: systems for decision support. 10th edition. Pearson.

Trieu, V. H., Burton-Jones, A., Green, P., & Cockcroft, S. (2022). Applying and extending the theory of effective use in a business intelligence context. MIS Quarterly, 46(1), 645-678.

Yang, H., Liu, X. Y., Zhong, S., & Walid, A. (2020). Deep reinforcement learning for automated stock trading: An ensemble strategy. In Proceedings of the first ACM international conference on AI in finance (pp. 1-8).