

International Training Programme

An Introduction to Artificial Intelligence

Foundations, Evolution, Frontiers,
and Applications

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中国援助
CHINA AID
FOR SHARED FUTURE

Wuhan, China
2026

About Myself

Education & Career

- **2010–2014:** B.E., Huazhong University of Science and Technology
- **2014–2016:** M.Sc., Université Paris-Saclay, France
- **2016–2019:** Ph.D., Université Paris-Saclay, France
- **2020–2021:** Postdoctoral researcher, UC Berkeley
- **2021–present:** Associate Professor, Huazhong University of Science and Technology, Wuhan. China

Field of expertise: machine learning, high-dimensional statistics, and efficient AI

Expertise & Professional Standing

- *Random Matrix Methods for Machine Learning*, Cambridge University Press, 2022
- **Area Chair:** ICML, NeurIPS, ICLR, and AISTATS; **Senior Program Committee:** AAAI
- 30+ publications, 1,400+ citations, reviewer for international grants: ERC, NSERC, NSFC, and ISF

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Three questions about AI

What can AI do?

Tasks, capabilities, and limitations.

Where do AI capabilities come from?

Rules, search, learning, and computation.

When is AI useful and reliable?

Evidence, evaluation, and real-world outcomes.

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What Is AI?

02

The AI Landscape

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How AI Evolved

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Applications and Judgment

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Further Resources

1 What AI Can Do Today

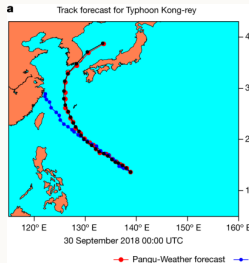
Language Assistant

User Summarize this report in three points.

AI 1. Demand rose.
2. Costs fell.
3. Risks remain.

Communicate

text → answer, summary, translation



Predict

weather data → typhoon



Act

sensors → physical actions

AI maps inputs to useful outputs: text to content, data to forecasts, sensors to actions.

Illustrative language interface; Bi et al. (2023), Fig. 4, CC BY 4.0; UBTECH company-provided industrial demonstration image.

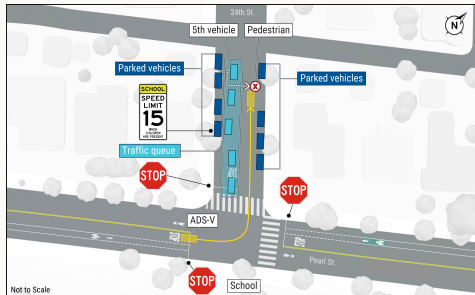
1 What AI Still Cannot Do Reliably

AI Generated Reference
13% found

plausible citation form $\neq$ verified source



one error can change every later step



Open-world traffic: parked vehicles + school zone

Fluent output, rare situations, and long task chains still require verifications, etc.

Reference-fabrication study (Gravel et al. 2023); NTSB preliminary ADS investigation HWY26FH008 (2026), U.S. federal work; course-drawn long-task schematic.

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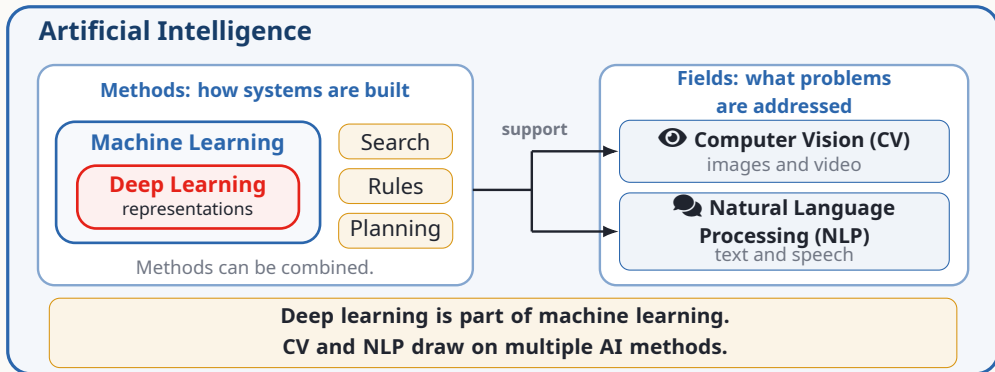
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Applications and Judgment

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Further Resources

How do methods, capabilities, and applications fit together?



Source: Terminology synthesized from Russell and Norvig (2021) and Bommasani et al. (2021).

Methods

How is it built?



Rules



Search



Machine learning

Capabilities

What can it do?

Perception Language processing Reasoning Generation Decision-making

Applications

Where is it used?



Healthcare



Manufacturing



Transport



Education



Science

Example: image recognition in healthcare

Method

Deep learning

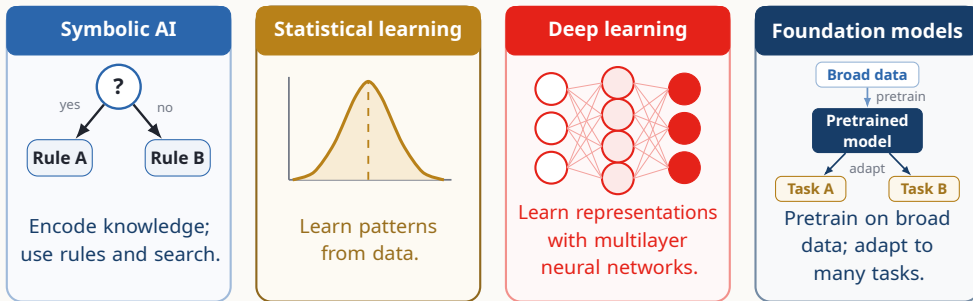
Capability

Image recognition

Application

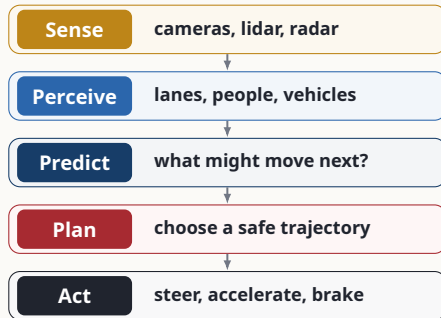
Healthcare

Overlapping approaches and model types



Deep learning is part of statistical machine learning.
Foundation models typically use deep learning.

Rules, search, and learning can be combined in one system.



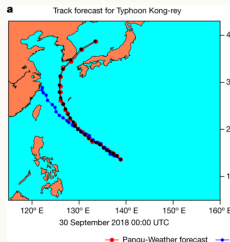
Apolong autonomous-shuttle photograph, People's Daily (2021); photograph is illustrative. Capability decomposition follows standard autonomous-driving stacks.

2 Applications define success



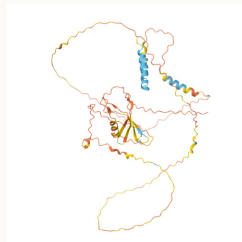
Manufacturing

quality, downtime, safe intervention



Weather

forecast skill, uncertainty, public safety



Science

reproducibility, validation, discovery

Application defines acceptable evidence, latency, cost, and consequence of error.

Shougang industrial setting, Beijing municipal image; Bi et al. (2023), Fig. 4, CC BY 4.0; AlphaFold DB structure rendering, CC BY 4.0.

Computer Vision (CV)

classify • detect • segment • track • measure



1 **Sense** moving fabric

2 **Locate a flaw** box or mask

3 **Name it** hole or broken yarn

4 **Respond** alert or stop the line

5 **Worker verifies and resolves**

Other objects: medical scans, satellite maps, traffic video

Fuzhou New Area Administrative Committee (2025); official case photographs. Deployment details are source-reported (Fuzhou New Area Administrative Committee 2025).

Natural Language Processing (NLP)

transcribe • translate • retrieve • generate



AI iFLYTEK

iFLYTEK (2025); official event photographs. Demonstrated functions and performance claims are company-reported (iFLYTEK 2025).

- 1 **Listen** live conference speech
- 2 **Transcribe** who said what
- 3 **Translate** across languages
- 4 **Display** real-time captions
- 5 **Summarize** draft meeting minutes
- 6 **Human checks**

Noise, accents, names, and specialist terms are important to the final result.

Prediction and recommendation

forecast • rank • match • recommend • optimize



Riders discuss delivery-time rules



Meituan (2021); official rider and product-screen images. Timing logic is platform-reported (Meituan 2021).

- 1 **Context** order, map, local info
- 2 **Estimate** each delivery segment
- 3 **Protect** model vs. timing rules
- 4 **Communicate** show an ETA window
- 5 **Update** restaurant runs late
- 6 **Rider/user** adjust plans

Robotics and embodied AI

localize • map • plan • navigate • recover

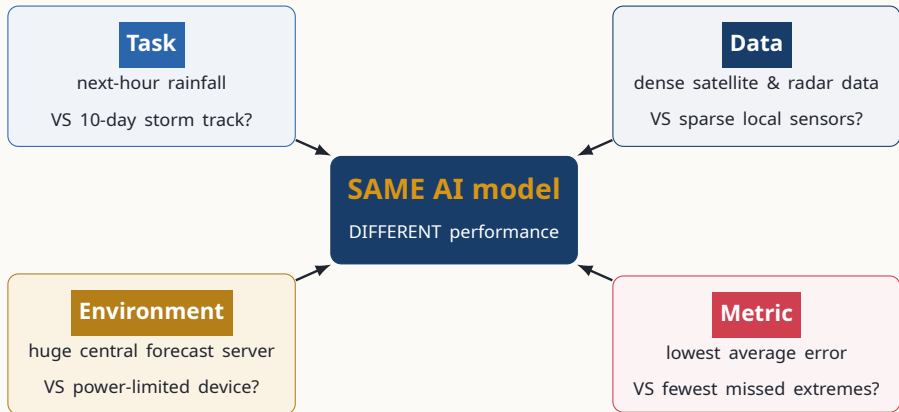


JD JD Logistics

JD Logistics (2024); official company photographs. System functions are company-reported (JD Logistics 2024).

- 1 Order** request an item
 - 2 Perceive** identify tote and shelf
 - 3 Plan** conflict-free route
 - 4 Act** move, lift, and deliver
 - 5 Picker verifies**
- Automation** repeats a defined sequence
- AI** selects or adapts under variation

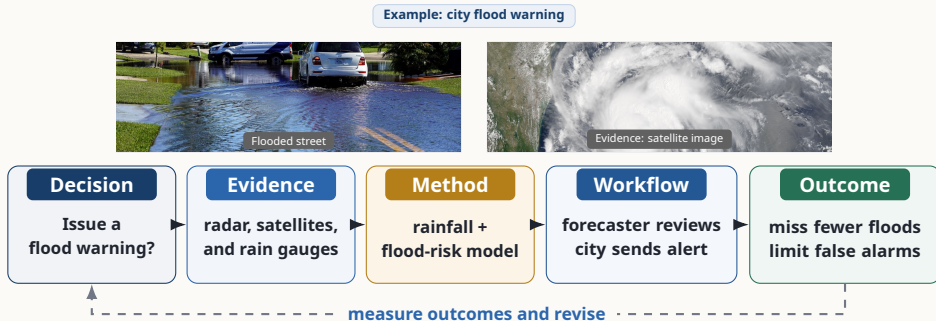
Conditions for evaluating AI performance



Same model may justify **different** conclusions in different scenarios

2

Start with the decision, not with the model



“Use AI”: **begin** with a decision, **connect** evidence to action, and **measure** the outcome.

Flooded street: Robert Kaufmann/FEMA, DVIDS photo 7447121 (2022), public domain; Hurricane Harvey: NASA Earth Observatory (2017), public domain.

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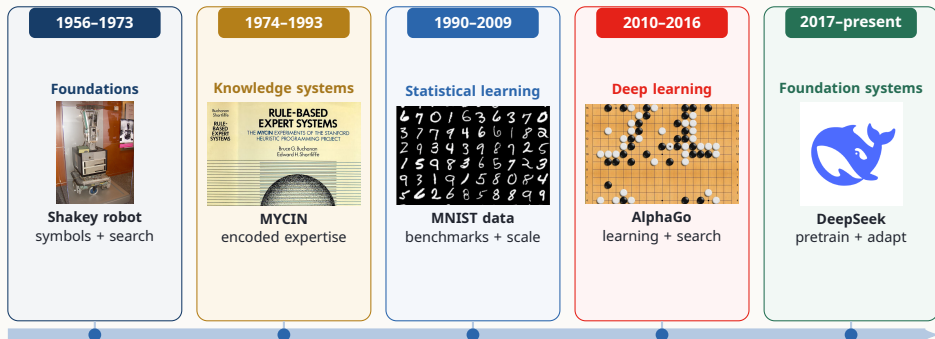
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Further Resources

How did these different approaches develop?

3

Five periods shaped the evolution of AI



Source: Representative visuals: Shakey, MYCIN, MNIST, AlphaGo, and DeepSeek; periodization based on Russell and Norvig (2021).



Scientists at the Dartmouth AI workshop, summer 1956. Photo: Margaret Minsky.

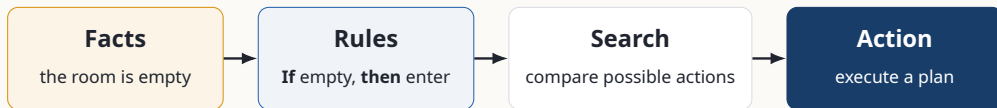
The lasting move

- treat intelligence as an engineering and scientific problem
- identify language, abstraction, learning, and self-improvement as research targets
- assume progress could come from precise mechanisms

The agenda was broad; the available **compute, data, and algorithms were NOT.**

Source: Photo: Margaret Minsky / Dartmouth Alumni Magazine; agenda: 1955 Dartmouth proposal (McCarthy et al. 1955).

3 Early AI emphasized symbols and search



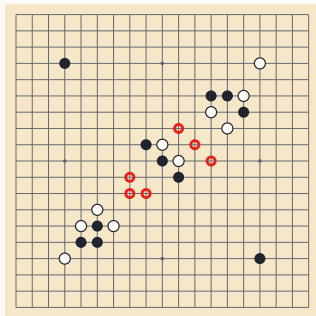
Strength Knowledge is **explicit**, understandable, compositional, and often inspectable.

Limit The world must FIRST be converted into symbols before reasoning can begin.

3

Go shows why search grows explosively

One Go position



Red rings show candidates; a typical position has around 250 (legal) moves.

$$N(d) = 1 + b + b^2 + \dots + b^d \approx b^d$$

b : choices per move d : look-ahead depth

1 move

$$250^1 = 250$$

2 moves

$$250^2 = 62,500$$

4 moves

$$250^4 \approx 3.9 \text{ billion}$$

10 moves

$$250^{10} \approx 9.5 \times 10^{23}$$

33 moves ahead: $250^{33} \approx 1.4 \times 10^{79}$
 Modern physics estimates about 10^{80} atoms
 in the observable universe.

How can we focus search on promising moves?

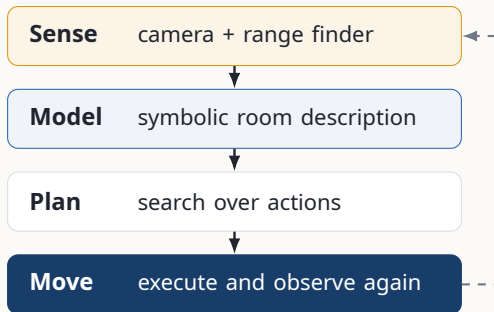
Source: Go branching factor: Silver et al. (2016); search complexity: Russell and Norvig (2021); atom estimate: NASA (2022).

3 Shakey linked perception to action



Carlo Nardone / Wikimedia Commons, CC BY-SA 2.0.

1966–1972 Shakey project

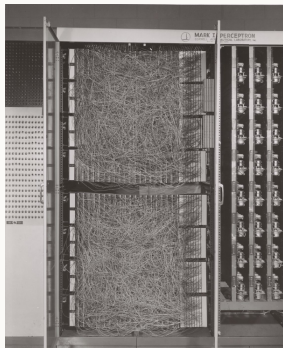


Shakey made AI visibly **systemic**: perception errors propagate into planning and action.

Source: Shakey project dates and historical context: Russell and Norvig (2021).

3 The perceptron opened a learning path

1957–1958 Perceptron proposed; Mark I built



Mark I Perceptron, U.S. Navy photograph; public domain.

$$\hat{y} = \text{sign}(w^T x + b)$$

- pixels become numerical inputs x
- weights w change after mistakes
- a linear boundary separates two classes

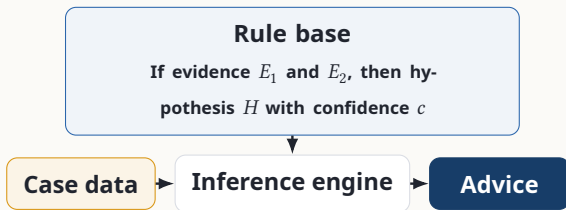
Learning from examples was present from the beginning of AI, but multilayer training was **NOT** yet practical.

Source: Perceptron dates and historical context: Russell and Norvig (2021).

3

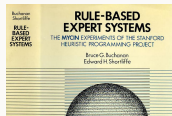
Expert systems scaled encoded knowledge

1976 MYCIN monograph



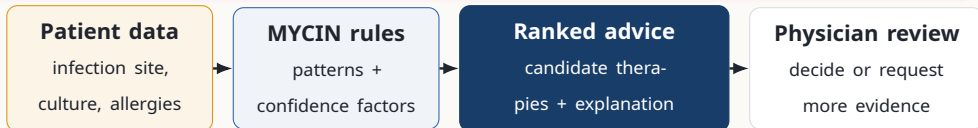
Knowledge bottleneck

- experts must articulate rules
- exceptions multiply
- expensive maintenance



MYCIN monograph, 1976

Problem: choose an initial antimicrobial treatment when evidence is incomplete.



Can useful patterns be learned from examples?

Source: MYCIN architecture and consultation example: Shortliffe (1976).

1974–1993 Knowledge systems

First winter: 1974–1980

- **Technical:** limited compute
- **Expectation:** promises outran evidence
- **Funding:** public support contracted

Second winter: 1987–1993

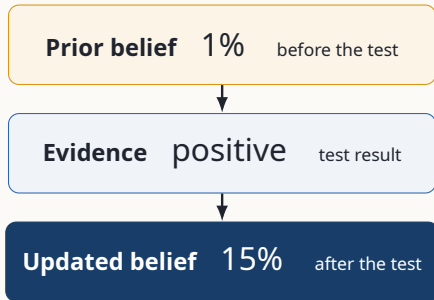
- **Technical:** costly maintenance
- **Market:** hardware sales collapsed
- **Expectation:** expert systems oversold



Winters correct expectations/investment, but do NOT stop research progress.

Source: Historical ranges and causes synthesized from Russell and Norvig (2021).

Illustrative medical-test example



Bayes' theorem

$$P(H | E) = \frac{P(E | H)P(H)}{P(E)}$$

- a **prior** records what was plausible before evidence
- **likelihood** describes how expected the evidence is
- the **posterior** updates confidence without claiming certainty

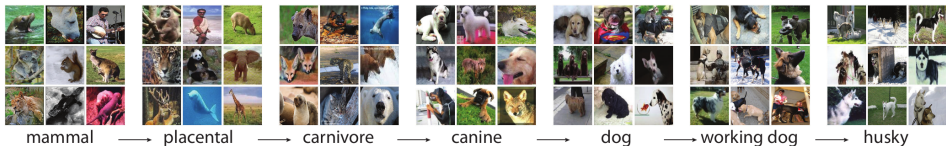
Probability turns “I am confident” into an explicit **quantity**.

Source: Illustrative Bayesian update; historical synthesis from Russell and Norvig (2021).

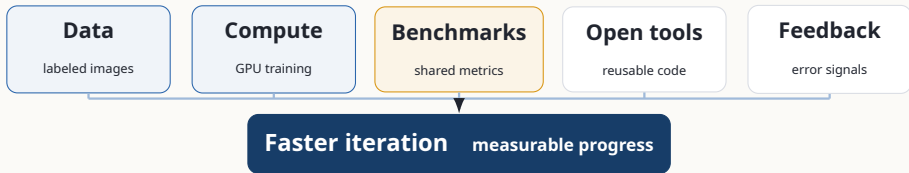
3

Data, compute, and benchmarks scaled AI

2009 ImageNet dataset published



A WordNet branch populated with real photographs: broad concepts → specific visual categories.

**Models learn patterns from examples.****Data, compute, and benchmarks support training and evaluation at scale.**

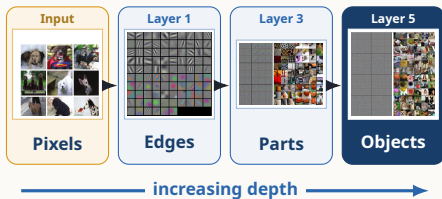
Results depend on the quality and coverage of the data.

Source: ImageNet hierarchy and sample photographs: Figure 1 in Deng et al. (2009); historical synthesis.

1990–2009 Statistical learning

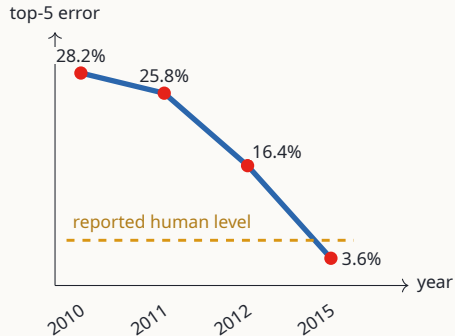
3 Deep learning transformed vision

2012 AlexNet changed the ImageNet trajectory



Depth = repeated composition

later layers combine earlier features
into more useful representations



1986 milestone

Backpropagation showed how hidden layers could learn useful representations.

2012 breakthrough

AlexNet combined deep convolutional networks, ImageNet data, and GPU training.

ImageNet results describe performance on a specific benchmark.

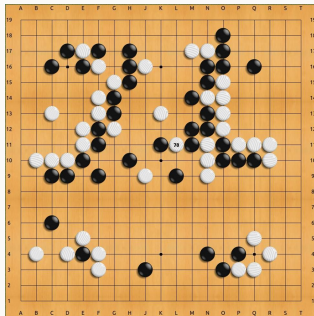
Source: ImageNet/Deng et al. (2009); Stanford CS231n; Zeiler-Fergus (2014); Rumelhart et al. (1986); Krizhevsky et al. (2012).

2010-2016 Deep learning

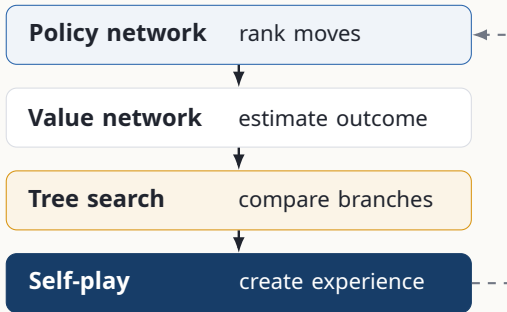
3

AlphaGo combined learning and search

2016 AlphaGo–Lee Sedol match



Game 4, Move 78 visualization by Axd; CC BY-SA 4.0.



**Learning ranks moves and evaluates positions,
helping search focus on promising branches.**

This system was trained and evaluated for Go.

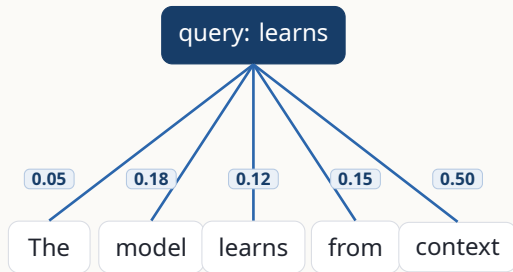
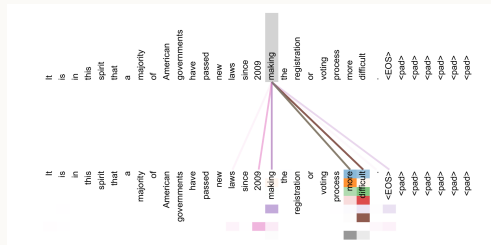
Source: System description: Silver et al. (2016).

2010–2016 Deep learning

3

Self-attention: representing tokens in context

2017 Transformer architecture



parallel training

long-range context

Challenge: Recurrent models process sequence positions one after another.

Advance: The Transformer uses self-attention to connect tokens directly and process positions in parallel during training.

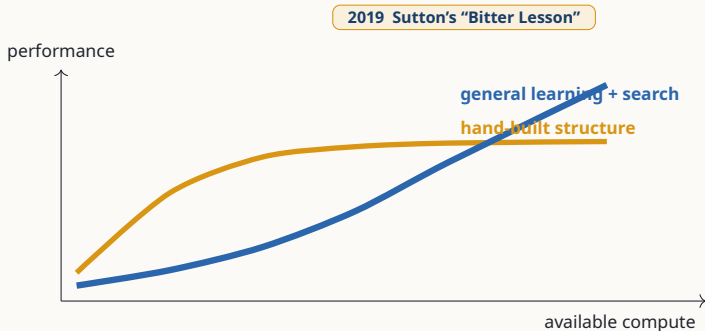
Text generation can still proceed one token at a time.

Source: Numeric example drawn for teaching; published attention head from Vaswani et al. (2017), Fig. 3.

2017-present Foundation systems

3

Scalable learning captures the bitter lesson



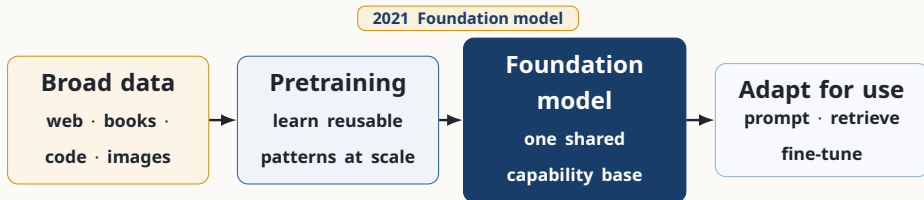
Richard S. Sutton
Reinforcement learning
pioneer

2019 The bitter lesson

Methods that can absorb **more computation and experience** often improve longer than methods capped by **human-crafted** knowledge.

Source: Sutton (2019); portrait: University of Alberta.

2017–present Foundation systems



Broad pretraining allows one model to be adapted to many tasks.

Each use still requires evaluation for its task and setting.

What “high-quality” meant in one published example

GPT-3 used filtered Common Crawl plus [WebText2](#), books, and Wikipedia.

WebText2 extended webpages selected via Reddit links.

ChatGPT 2022

A GPT-3.5-series foundation model adapted for dialogue and human preferences.

Modern AI combines earlier ideas with advances in data, training, and computation.

Source: (Bommasani et al. 2021; Brown et al. 2020; OpenAI 2019; OpenAI 2022).

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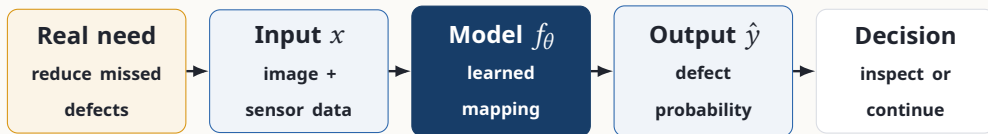
Applications and Judgment

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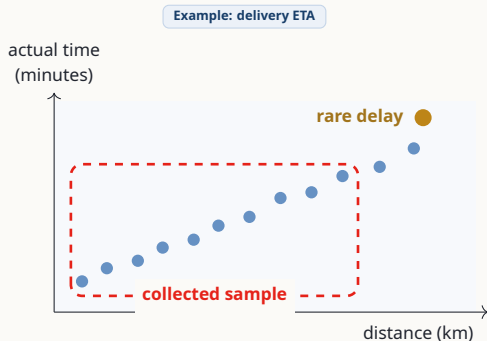
How are model parameters learned from data?

4 Define the task before training



Define: a target, a measurable error, and a decision that can improve.

4 A dataset is only a sample



Each record contains

Input x delivery distance

Target y observed delivery time

Context traffic, weather, etc.

Ask what is missing: locations, busy periods, unusual weather, or long delays.

Source: Illustrative synthetic delivery data; sampling perspective from Russell and Norvig (2021).

4

Model: linear regression for delivery time

Example: delivery ETA

$$\hat{y} = f_w = w_0 + w_1 x$$

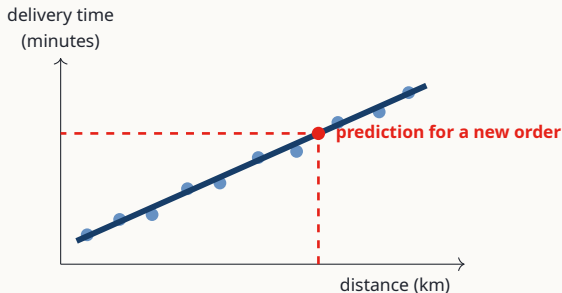
x delivery distance

$\hat{y}$ predicted time

w_0 preparation and fixed overhead

w_1 added time per kilometre

Real ETA also depends on traffic, weather, preparation, and routing.



Source: Illustrative synthetic data; linear-model framing from Russell and Norvig (2021).

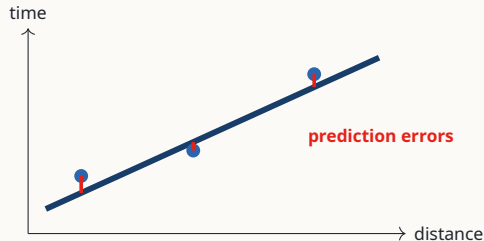
4

Loss: MSE defines what “better” means

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

Actual	Predicted	Error ²
14 min	16 min	4
22 min	20 min	4
29 min	25 min	16

$$\text{MSE} = 8 \text{ min}^2$$



Source: Illustrative calculation; standard regression objective from Russell and Norvig (2021).

4 Optimization: gradient descent

$$w(t+1) = w(t) - \eta \cdot \Delta \text{MSE}_w(t)$$

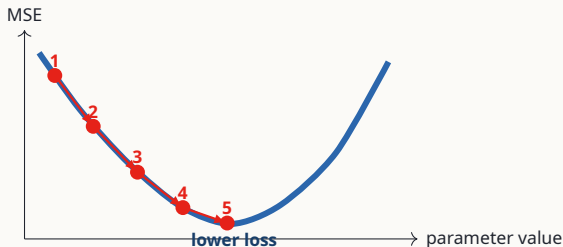
Parameters current position

Gradient direction to increase error

Learning rate η size of each update

η too small
slow progress

η too large
may overshoot



Source: Optimization intuition; see Russell and Norvig (2021).

Model

what can be represented

- Linear regression
- Trees and random forests
- Neural nets and beyond

Loss

which mistakes matter

- MSE for regression
- MAE / Huber for outliers
- Cross-entropy for classes

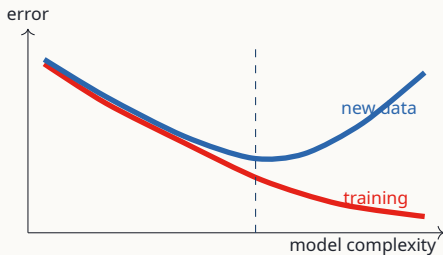
Optimizer

how parameters move

- Gradient descent
- Mini-batch SGD
- Adam / AdamW

Task sets the target; model sets possibilities; loss scores errors; optimizer searches.

Source: Examples synthesized from standard machine-learning practice; see Russell and Norvig (2021).



Three regimes

Underfit misses even training patterns

Good fit captures patterns that repeat

Overfit memorizes quirks that do not repeat

Low training error proves optimization, NOT necessarily test or deployment reliability.

4

Four learning schemes use different feedback

Supervised learning



Signal: human-provided labels

Examples: linear classification, linear regression

Self-supervised learning



Signal: targets constructed from the data

Examples: masked prediction, contrastive learning

Unsupervised learning



Signal: no target labels

Examples: k-means clustering, PCA

Reinforcement learning

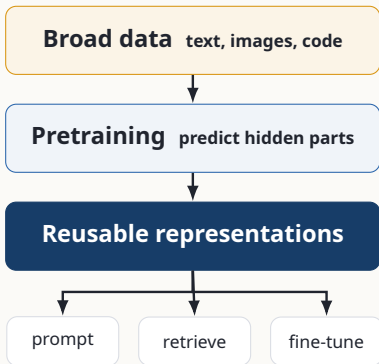


Signal: rewards after actions

Examples: Q-learning, policy gradients

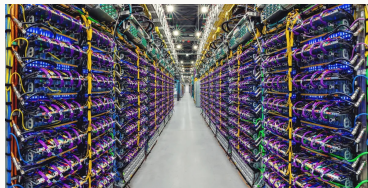
Source: Course-drawn diagrams; apple: Roma05082010 / Wikimedia Commons, public domain; robot: [Google DeepMind RGB-Stacking \(2021\)](#); taxonomy: Russell and Norvig (2021).

Pretraining: learning reusable representations



Input: The man went to the [MASK]₁ . He bought a [MASK]₂ of milk .
Labels: [MASK]₁ = store; [MASK]₂ = gallon

Self-supervised signal: predict words hidden by [MASK] . Google Research (2018).

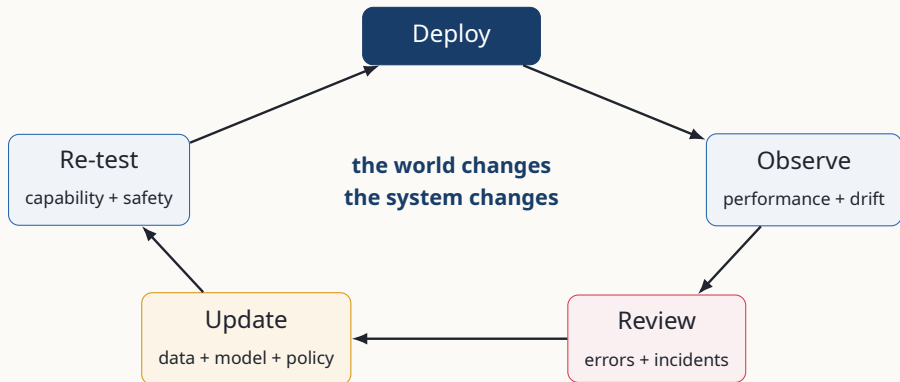


Cloud TPU v5p systems used for large-scale AI training. Google (2023).

Reuse reduces data needed for new tasks, but evaluation remains task-specific.

Source: Lifecycle: Bommasani et al. (2021); BERT example: Google Research (2018); TPU photograph: Google (2023).

Deployment begins a new feedback loop



Source: Lifecycle framing informed by National Institute of Standards and Technology (2023).

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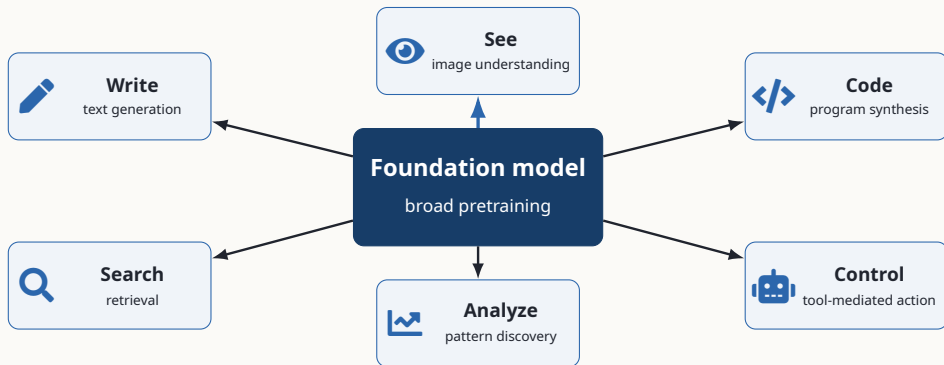
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Further Resources

How can AI handle broader and more complex tasks?



Source: Foundation-model framing: Bommasani et al. (2021).

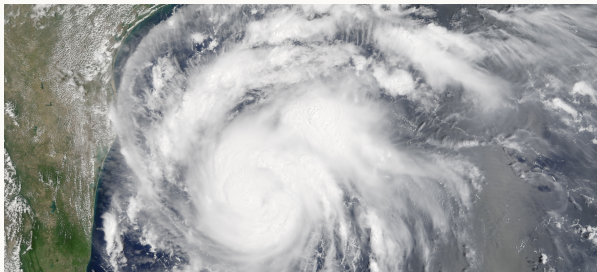


Image input: a tropical cyclone over the Gulf of Mexico

Image + question

Question: what is happening in this image?



Text output

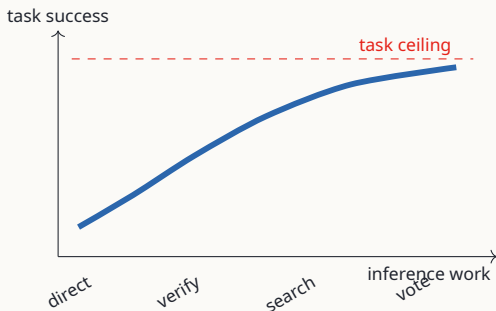
A tropical cyclone is organizing over warm ocean. Track and intensity require additional weather data.

Multimodal AI connects **visible (or other kind of) evidence to a question and an answer.**

NASA Earth Observatory, Hurricane Harvey; public-domain U.S. federal image.

5

More inference can improve reasoning



Tool-assisted example

? What is 17% of ¥860?

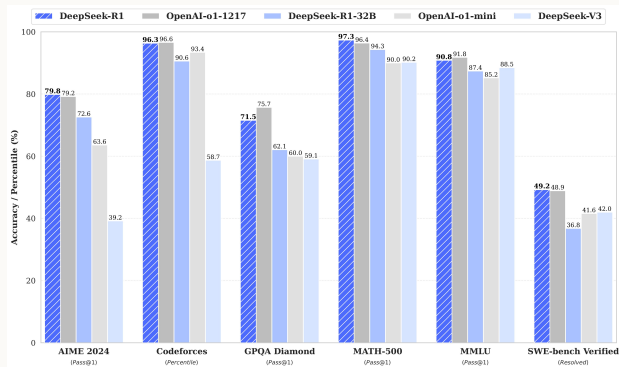
$\frac{1}{2}$ $\equiv$ Set up 860×0.17

Calculator returns 146.2

✓ Answer: ¥146.20

The model chooses the calculation; the tool executes it; verification checks units and meaning.

Source: Inference-scaling framing: DeepSeek-AI et al. (2025).



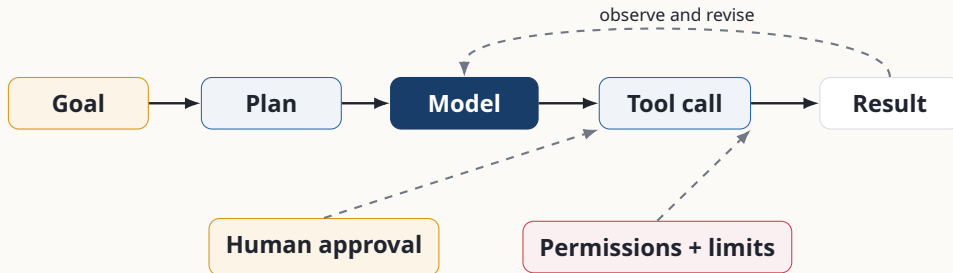
Read the bars

- each cluster is a different benchmark
- models vary by task
- bars report the paper's evaluation setup

Benchmark performance is not deployment reliability.

DeepSeek-AI, DeepSeek-R1 repository and paper; benchmark image distributed with the MIT-licensed repository (DeepSeek-AI et al. 2025).

5 AI agents: tools, workflows, and oversight



An agent is a system design: model, state, tools, permissions, monitoring, and recovery.

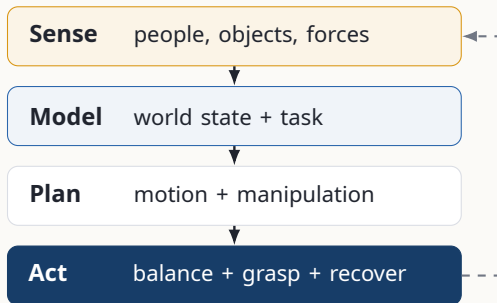
Source: Tool loop: Yao et al. (2023); agent framing: Xi et al. (2025).

5 Perception, planning, and action in embodied AI

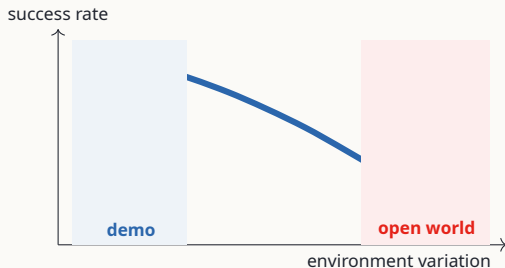


UB UBTECH

UBTECH Walker S product documentation and company-provided image; demonstrated capabilities remain company-reported (UBTECH Robotics 2026).



5 Humanoid robots face a reliability gap



The gap includes

- long-tail objects and layouts
- hardware wear and latency
- safe contact with people
- recovery after partial failure

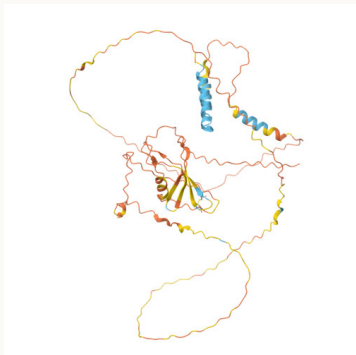
A demo may answer “yes I can.”

Deployment asks how often, where, and with what recovery.



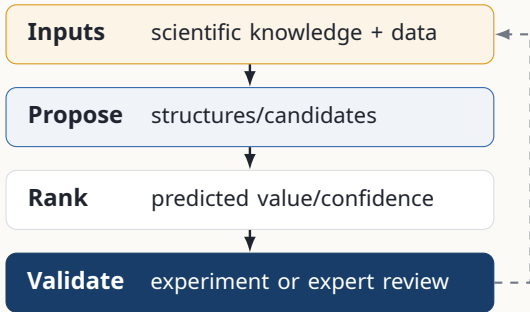
[Atlas failure footage on Bilibili](#)

Source: Reliability framing: Duan et al. (2022); classroom video: [Atlas parkour failures, Bilibili \(2021\)](#).

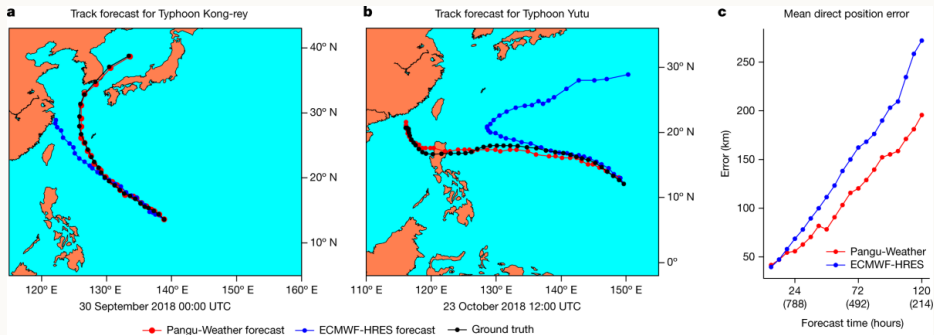


Predicted protein structure

AlphaFold DB structure rendering.



Prediction can prioritize experiments; but does **NOT** replace experimental evidence.



Red: Pangu-Weather forecast Blue: ECMWF-HRES forecast Black: observed track

The figure compares forecast tracks and position error.

Bi et al., Nature 619 (2023), Fig. 4; CC BY 4.0 (Bi et al. 2023).

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Frontiers of AI

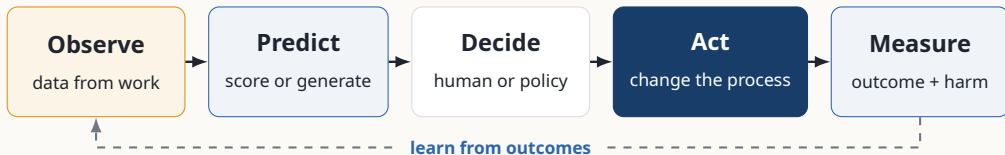
06

Applications and Judgment

07

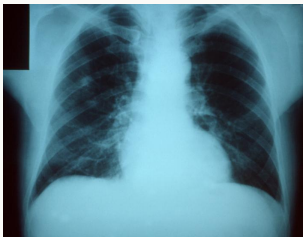
Further Resources

What turns an AI capability into a useful service?



A model creates value only when its output **improves** a decision and the outcome is **measured**.

6 AI scores support clinical decisions



Real chest X-ray; illustrative AI score: 0.82

AI score pneumonia risk: 0.82

Evidence symptoms + history + tests

Decision accept, reject, or further investigate

Outcome patient benefit & harm

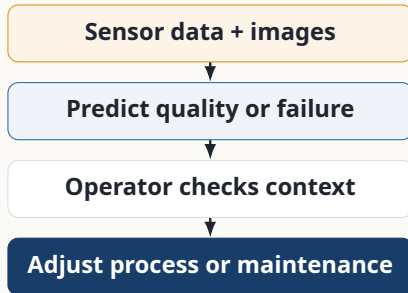
Clinicians may disagree.

Source: Healthcare governance principles: World Health Organization (2024); X-ray: CDC Public Health Image Library via Wikimedia Commons.

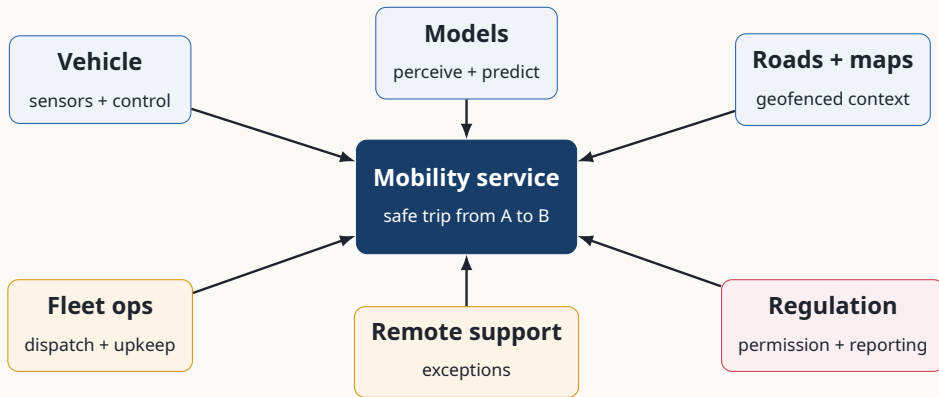


Physical process: a steel blast-furnace installation

Shougang industrial setting, Beijing municipal image. China Baowu case context: official reporting and MIIT case identification (Ministry of Industry and Information Technology of the People's Republic of China 2026).



■ CHINA BAOWU The industrial object is visible; performance still has to be measured as quality, downtime, energy, or safety.





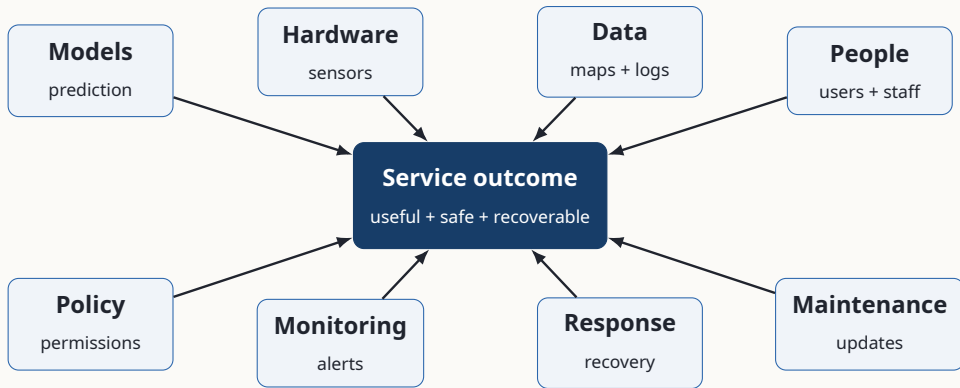
Autonomous shuttle platform: illustrative photograph

Apolong autonomous shuttle visual, People's Daily (2021). Wuhan context: municipal transport documents (Wuhan Municipal Transportation Bureau 2025).

Wuhan deployment context Baidu

- approved operating areas and staged permissions
- fleet operations and remote assistance
- road, weather, mapping, and reporting dependencies

The evidence concerns a **bounded** operating system, not unrestricted autonomy on every road.



6 Four questions before choosing AI

1. What decision should improve?

2. Is the evidence representative?

3. What counts as success or failure?

4. Who can intervene and repair harm?

A strong candidate

Predict machine failure; abundant sensors; downtime measurable; operator can override.

A weak candidate

“Score human potential”; vague target; biased history; life-changing consequences.

Source: Course judgment framework; risk concepts informed by National Institute of Standards and Technology (2023).

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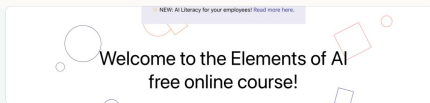
Applications and Judgment

07

Further Resources

How can we start learning and building with AI?

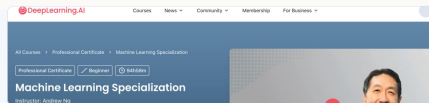
Online courses for different starting points



Elements of AI

No coding required

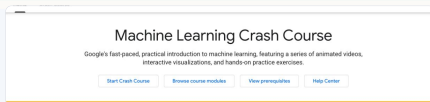
 elementsofai.com



Machine Learning Specialization

Guided foundation

 deeplearning.ai



Google ML Crash Course

Interactive review

 developers.google.com/ml

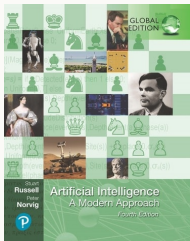


fast.ai Practical Deep Learning

Build models early

 course.fast.ai

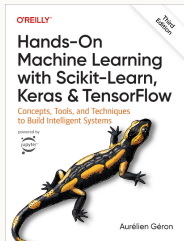
Source: Official course-page screenshots, accessed September 2026. Course access and certificate terms may change.



Breadth

AIMA, 4e

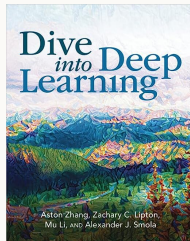
Russell and Norvig



Practice

Hands-On ML, 3e

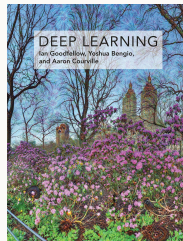
Aurélien Géron



Interactive

Dive into Deep Learning

Zhang, Lipton, Li, Smola



Theory

Deep Learning

Goodfellow, Bengio, Courville

Start with Hands-On ML or D2L; keep AIMA and Deep Learning as references.

Source: Official publisher and project cover images: Pearson, O'Reilly, D2L, and MIT Press.

Core workflow



Python + Jupyter
code and experiments



python.org



jupyter.org



NumPy + pandas
arrays and tables



numpy.org, pandas.pydata.org



scikit-learn
classical ML



scikit-learn.org

Add for the task



PyTorch
neural networks



pytorch.org/tutorials



Hugging Face
models and datasets



huggingface.co/learn



OpenCV
images and video



opencv.org

A useful first stack is Jupyter, pandas, and scikit-learn. Add PyTorch when neural networks are needed.



UCI ML Repository

Well-documented datasets for first classification and regression experiments.

archive.ics.uci.edu



arXiv cs.LG

Recent preprints in machine learning. A preprint may not have passed peer review.

arxiv.org/list/cs.LG/recent



OpenML

Datasets, defined tasks, APIs, and reproducible benchmark runs.

openml.org



Papers with Code

Links among papers, code, datasets, and benchmark tables.

paperswithcode.com

Before reusing sth., check the data license, metric, and eval. conditions.



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Thank You! Any question?

8 Appendix: learning setups

Setup	Feedback	Typical question	Example
Supervised	labeled input-output pairs	What output should this input have?	defect classification
Semi-supervised	few labels + much unlabeled data	Can unlabeled structure improve a labeled task?	medical imaging with scarce annotations
Unsupervised	no target labels	What structure or groups exist?	exploratory clustering
Self-supervised	targets constructed from the data	Can hidden or future parts be predicted?	language-model pretraining
Reinforcement learning	reward after actions	Which behavior improves long-term return?	control or reasoning-behavior shaping

The setup is determined by the available feedback.

Source: Taxonomy: Russell and Norvig (2021); reasoning example: DeepSeek-AI et al. (2025).

8 Appendix: system evaluation matrix

Dimension	Core question	Example measures	Frequent mistake
Capability	Does it perform the intended task?	accuracy, quality, task success	using a convenient benchmark
Robustness	Does it hold under relevant change?	subgroup, shift, edge-case tests	reporting only the average
Efficiency	Is the benefit worth the resources?	latency, energy, compute, cost	ignoring full workflow cost
Safety	Can harm be prevented and repaired?	red-team tests, access logs, incidents	treating refusal rate as complete safety
Governance	Who can decide, intervene, and appeal?	ownership, audit trail, remedy	responsibility without authority

Source: Evaluation synthesis; risk-management structure informed by National Institute of Standards and Technology (2023).

8 Appendix: China case evidence

Case	Evidence type	What it supports	What it does not establish
DeepSeek-R1	peer-reviewed paper + open artifacts	training stages and reported evaluations	universal reasoning reliability
Baowu furnace operator	MIIT case-list identification	existence of an industrial AI case	independent operational performance
UBTECH Walker	corporate profile / reporting	stated deployments and milestones	independently verified uptime at scale
Pangu-Weather	peer-reviewed Nature paper	method and evaluation under study conditions	replacement of operational forecasting systems
Apollo Go in Wuhan	municipal regulatory/operating documents	commercial-pilot context and system dependencies	unrestricted general autonomy

Source: DeepSeek-AI et al. (2025); Ministry of Industry and Information Technology of the People's Republic of China (2026); UBTECH Robotics (2026); Bi et al. (2023); Wuhan Municipal Transportation Bureau (2025).

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