TECHNICAL REPORT

ISO/IEC TR 24372

First edition
2021-12

Information technology — Artificial intelligence (AI) — Overview of computational approaches for AI systems

Reference number
ISO/IEC TR 24372:2021(E)

ISO copyright office
CP 401 • Ch. de Blandonnet 8
CH-1214 Vernier, Geneva
Phone: +41 22 749 01 11
Email: copyright@iso.org
Website: www.iso.org

Published in Switzerland

Contents

Page

Foreword

ISO (the International Organization for Standardization) and IEC (the International Electrotechnical Commission) form the specialized system for worldwide standardization. National bodies that are members of ISO or IEC participate in the development of International Standards through technical committees established by the respective organization to deal with particular fields of technical activity. ISO and IEC technical committees collaborate in fields of mutual interest. Other international organizations, governmental and non-governmental, in liaison with ISO and IEC, also take part in the work.

The procedures used to develop this document and those intended for its further maintenance are described in the ISO/IEC Directives, Part 1. In particular, the different approval criteria needed for the different types of document should be noted. This document was drafted in accordance with the editorial rules of the ISO/IEC Directives, Part 2 (see www.iso.org/directives or www.iec.ch/members_experts/refdocs).

Attention is drawn to the possibility that some of the elements of this document may be the subject of patent rights. ISO and IEC shall not be held responsible for identifying any or all such patent rights. Details of any patent rights identified during the development of the document will be in the Introduction and/or on the ISO list of patent declarations received (see www.iso.org/patents) or the IEC list of patent declarations received (see https://patents.iec.ch).

Any trade name used in this document is information given for the convenience of users and does not constitute an endorsement.

For an explanation of the voluntary nature of standards, the meaning of ISO specific terms and expressions related to conformity assessment, as well as information about ISO's adherence to the World Trade Organization (WTO) principles in the Technical Barriers to Trade (TBT) see www.iso.org/iso/foreword.html. In the IEC, see www.iec.ch/understanding-standards.

This document was prepared by Joint Technical Committee ISO/IEC JTC 1, *Information technology*, Subcommittee SC 42, *Artificial intelligence*.

Any feedback or questions on this document should be directed to the user’s national standards body. A complete listing of these bodies can be found at www.iso.org/members.html and www.iec.ch/national-committees.

Introduction

Artificial intelligence (AI)-related products, systems and solutions have become more common in recent years thanks to rapid software and hardware improvements that boost computational performance, data storage capabilities and network bandwidth. The intent of this document is to look at computational methods and approaches within AI systems. Based on ISO/IEC 22989[1], ISO/IEC 23053[2] and ISO/IEC TR 24030, this document provides a description of the characteristics of an AI system and its computational approaches. The illustration of computational approaches in AI systems includes both machine learning and non-machine learning methods. To reflect state-of-the-art methods used in AI, this document is structured as follows:

— Clause 5 provides an overall description of computational approaches in AI systems;

— Clause 6 discusses the main characteristics of AI systems;

— Clause 7 provides a general taxonomy of computational approaches, including knowledge-driven and data-driven approaches;

— Clause 8 discusses selected algorithms used in AI systems, including basic theories and techniques, main characteristics and typical applications.

By giving an overview of different technologies used by AI systems, this document is intended to help users understand computational characteristics and approaches used in AI.

1) Under preparation. Stage at the time of publication: ISO/IEC DIS 22989:2021.

2) Under preparation. Stage at the time of publication: ISO/IEC DIS 23053:2021.

Information technology — Artificial intelligence (AI) — Overview of computational approaches for AI systems

1 Scope

This document provides an overview of the state of the art of computational approaches for AI systems, by describing: a) main computational characteristics of AI systems; b) main algorithms and approaches used in AI systems, referencing use cases contained in ISO/IEC TR 24030.

2 Normative references

The following documents are referred to in the text in such a way that some or all of their content constitutes requirements of this document. For dated references, only the edition cited applies. For undated references, the latest edition of the referenced document (including any amendments) applies.

ISO/IEC 22989, *Information technology — Artificial intelligence — Artificial intelligence concepts and terminology*

ISO/IEC 23053, *Framework for artificial intelligence (AI) systems using machine learning (ML)*

3 Terms and definitions

For the purposes of this document, the terms and definitions given in ISO/IEC 22989 and ISO/IEC 23053 and the following apply.

ISO and IEC maintain terminology databases for use in standardization at the following addresses:

— ISO Online browsing platform: available at https://www.iso.org/obp

— IEC Electropedia: available at https://www.electropedia.org/

3.1
heuristic search
search, based on experience and judgment, used to obtain acceptable results without guarantee of success

[SOURCE: ISO/IEC 2382:2015, 2123854, modified — Notes to entry removed.]

3.2
fuzzy logic
fuzzy-set logic
nonclassical logic in which facts, inference rules and quantifiers are given certainty factors

[SOURCE: ISO/IEC 2382:2015, 2123795, modified — Notes to entry removed.]

3.3
generator
neural network that produces samples usually to be classified by a discriminator

Note 1 to entry: Generators primarily appear in the context of generative adversarial networks.

3.4
discriminator
neural network that classifies samples usually produced by a generator

Note 1 to entry: Discriminators primarily appear in the context of generative adversarial networks.

3.5
generative adversarial network
GAN
neural network architecture comprised of one or more generators and one or more discriminators that compete to improve model performance

3.6
platform
combination of an operating system and hardware that makes up the operating environment in which a program runs

[SOURCE: ISO/IEC/IEEE 26513:2017, 3.30]

3.7
perceptron
neural network consisting of one artificial neuron, with a binary or continuous output value that is determined by applying a monotonic function to a linear combination of the input values and with error-correction learning

Note 1 to entry: The perceptron forms two decision regions separated by a hyperplane.

Note 2 to entry: For binary input values, the perceptron cannot implement the non-equivalence operation (EXCLUSIVE OR, XOR).

[SOURCE: ISO/IEC 2382:2015, 2120656, modified — term revised, "or continuous" added to definition and Notes 3 and 4 to entry removed.]

4 Abbreviated terms

AI	artificial intelligence
ASIC	application-specific integrated circuit
BERT	bidirectional encoder representations from transformers
BPTT	back propagation through time
CNN	convolutional neural network
CPU	central processing unit
DAG	directed acyclic graph
DNN	deep neural network
ERM	empirical risk minimization
FFNN	feedforward neural network
FPGA	field programmable gate array
GDM	gradient descent method
GPU	graphics processing unit

GPT	generative pre-training
IoT	internet of things
KG	knowledge graph
KNN	k-nearest neighbour
LSTM	long short-term memory
MFCC	Mel-frequency cepstrum coefficient
MLM	masked language model
NER	named entity recognition
NLP	natural language processing
NSP	next sentence prediction
OWL	web ontology language
QA	question answering
RDF	resource description framework
RNN	recurrent neural network
RTRL	real-time recurrent learning
SPARQL	SPARQL protocol and RDF query language
SQL	structured query language
SRM	structure risk minimization
SVM	support vector machine
URI	uniform resource identifier
XML	extensible markup language

5 General

Advances in computational approaches are an important driving force in the maturation of AI to become capable of processing various tasks. Initial AI methods were primarily rules-based and knowledge-driven. More recently, data-driven methods such as neural networks have gained prominence. AI computational approaches continue to evolve in industry and academia and are an important consideration in AI systems.

Computational approaches for AI systems are often categorized based on various criteria. One such categorization is by the purpose of the AI system. This purpose-based categorization is adapted from studies of AI[1] and includes an exemplary categorization of common types.

a) Search methods. These approaches can be further divided into various types of search: classical, advanced search algorithms, adversarial search and constraint satisfaction.

   1) Classical search algorithms solve problems by a search over some state space and can be divided into uninformed searches and heuristic searches, which apply a rule of thumb to guide and speed up the search.

2) Advanced search algorithms include those that search in a local subspace, those that are nondeterministic, those that search with partial observation of the search space and online versions of search algorithms.

3) Adversarial search algorithms search in the presence of an opponent and are generally used in games. These include notable algorithms such as alpha-beta pruning and also include stochastic and partially observable variations.

4) Constraint satisfaction problems are solved when each variable in the problem has a value that satisfies all the constraints.

b) Logics, planning and knowledge. These approaches can be further divided into three cases: logics, planning and state space search, and knowledge representation.

1) Logics, such as propositional logic and first-order logic, are used in classical AI to represent knowledge. Problem solution in such computational systems involves inference over the logic using algorithms such as resolution.

2) Planning in classical AI systems involves search over some state space as well as algorithmic extensions to deal with planning in the real world. Methods to deal with the complexity of real-world planning involve time and resource constraints, hierarchical planning where problems are solved at abstract levels first before fine-grain details, multi-agent systems that handle uncertainties and dealing with other agents in the system.

3) Knowledge representation is a kind of data structure for describing knowledge using predicate logic, “if-then” generation and knowledge frame representation.

c) Uncertain knowledge and reasoning. Approaches in this area deal with potentially missing, uncertain or incomplete knowledge. They generally use either probability or fuzzy logic to represent concepts. Probabilistic computational systems reason using Bayes rule, Bayesian networks or (in time-dependent situations) hidden Markov models or Kalman filters. Another set of computational approaches is used for decision-making, including those based on utility theory and decision networks.

d) Learning. Computational approaches in this area deal with the problem of making the computer learn similarly to a human. Approaches can be grouped into learning from examples, knowledge-based learning, probabilistic learning, reinforcement learning, deep learning approaches, GANs and other learning approaches.

1) Learning from examples involves supervised learning approaches that learn a machine learning model from labelled data. It includes methods such as decision trees, linear and logistic regression approaches, artificial neural networks, non-parametric approaches (e.g. the KNN), SVMs and ensemble learning methods (e.g. bagging, boosting and variants of random forest).

2) Knowledge-based learning approaches include logic-based approaches, explanation-based learning and inductive logic programming.

3) Probabilistic learning involves computational approaches such as Bayesian methods and expectation-maximization methods.

4) Reinforcement learning involves computational systems that receive feedback, make decisions and take actions in environments to maximize the overall reward. Notable algorithms include temporal difference-learning and Q-learning.

5) Deep learning neural approaches involve modern computational approaches with many hidden layers, including deep feedforward networks, regularisation, modern optimization methods, CNNs and sequence learning methods such as LSTM networks.

6) GANs involve two competing networks, a generator and discriminator. The generator produces samples and the discriminator classifies each sample as real or fake. After this iterative process, trained generators can be used in applications such as creating artificial images.

7) Other learning approaches include unsupervised learning, which involves identifying the natural structure of data sets; semi-supervised learning, which deals with partially labelled data sets; online learning algorithms, which continue to learn as they receive data; networks and relational learning, ranking and preference learning, representation learning, transfer learning and active learning.

e) Inference. These approaches embody the application of an AI system in estimating parameters or aspects of (or classifying new or unobserved data based on) learned, acquired or defined parameters. Bayesian inference is the act of taking statistical inference from a Bayesian point of view. Approximate inferences, such as variational inference, solves the inference problem by taking the best approximation of the statistics. Monte Carlo algorithms generate samples from a known distribution that is difficult to normalize, then infer statistics from generated samples. Causal inference involves inferencing the causal connections of the observed data.

f) Dimensionality reduction. These computational approaches involve reducing the number of dimensions of data by either dimensionality reduction (feature extraction) algorithms, which identify a new smaller number of attributes to represent data, or feature selection, which chooses a subset of the most appropriate attributes.

g) Communicating, perceiving and acting. Computation approaches in these areas are associated with the fields of NLP (including tasks such as language modelling, text classification, information retrieval, information extraction, parsing, machine translation and speech recognition), computer vision (including image processing and object recognition) and robotics.

These categories and subcategories are not mutually exclusive. For instance, deep learning approaches [d)5)] can be either supervised [d)1)] or unsupervised [d)7)], reinforcement learning [d)4)] can be achieved through deep learning [d)5)], and approaches for machine translation or object recognition [g)] can be learning approaches [d)].

ISO/IEC 22989 specifies concepts and terminologies relevant to AI computational approaches. ISO/IEC 23053 provides a framework for AI systems using machine learning, encompassing machine learning algorithms, optimization algorithms and machine learning methods. ISO/IEC TR 24030 collects and analyses AI use cases.

6 Main characteristics of AI systems

6.1 General

Not all AI systems are based on machine learning or neural networks. To demonstrate the breadth of AI systems, some frequently encountered characteristics of AI systems are described in 6.2 and 6.3. These characteristics are broadly conceptual and not tied to a specific methodology or architecture. In the aggregate these characteristics differentiate AI systems from non-AI systems.

Some characteristics of AI systems are common and apply widely to different use cases. Others are specific to a small number of use cases within a specific industry. This clause contains a list of characteristics of AI systems which is not exhaustive but contains attributes intrinsic to many AI systems. While the list is not limited to a specific base technology (such as AI systems built with neural networks), it does not encompass every type of dynamic AI system.

6.2 Typical characteristics of AI systems

6.2.1 Adaptable

Some AI systems adapt to different changes in itself and the environment in which it is deployed. Such adaptation depends on many factors, including data in the system's domain, architecture or other technical decisions made at its implementation.

AI systems often operate on server-side cloud computing environments with access to high-performance computing and other resources. With the growth of IoT systems capable of general-purpose computing on GPUs and multi-core CPUs, or AI processing on application-specific processors and accelerators, AI system adaptability now extends to IoT implementation considerations, such as near-real-time data processing, optimization for low latency and power-efficient performance.

6.2.2 Constructive

Some AI systems construct or generate a static or dynamic output based on specified input criteria. This applies to methods including unsupervised learning and generative learning.

6.2.3 Coordinated

Some AI systems coordinate between agents. Agents can also be AI systems in their own right, but do not need to be. Many simultaneous constraints can govern agent behaviour, including static or dynamic ways. Coordination can be exhibited either explicitly through direct negotiation among the systems or implicitly through reaction to changes in the environment.

6.2.4 Dynamic

Some AI systems exhibit dynamic decision-making based on external data sources. These data sources can come from other software platforms, from physical environments or from other sources.

6.2.5 Explainable

Some AI systems provide a mechanism to explain what precipitated a decision or output. This output can take many forms and can be explicit or implicit with respect to AI system design.

An explainable AI system can contribute to or complement trustworthiness, accuracy and efficiency. Explainability can also contribute to comparison and optimization of machine learning model performance by generating insights into factors that degrade performance. Explainability can be an important counter to deceptive behaviour in AI systems.

6.2.6 Discriminative or generative

Some AI systems are discriminative, designed primarily to distinguish between possible outputs such as by excluding prior probabilities. Alternatively, some AI systems are generative, designed primarily to represent relevant aspects of data, such as by including prior probabilities.

6.2.7 Introspective

Some AI systems self-monitor to adapt to their environment or to provide insight into their functionality, such as in an audit situation. This self-monitoring can be adaptable, situation-dependent or static, and can take different forms depending on the system architecture.

To support introspective AI systems, performance monitoring functionality collects and reports performance metrics regarding CPU, GPU or application-specific processor compute resources, memory and other system resource usage. This information can be used to configure AI system resources, such as memory allocation, kernel configuration and load balancing across a multi-processor or hybrid hardware system, and enable an AI system to handle parallelization and acceleration for machine learning model training or inference.

6.2.8 Trained or trainable

Some AI systems are trained on a data set before deployment or trained dynamically (through adaptation) as the system is used. Systems with these characteristics have numerous possible system architectures (e.g. neural networks, hidden Markov models).

6.2.9 Accommodating various data

Some AI systems deal with large amounts of heterogeneous data that are structured or unstructured, static or streaming. AI systems can draw insights from varied data sets to help humans make better and more accurate decisions.

6.3 Computational characteristics of AI systems

6.3.1 Data-based or knowledge-based

A characteristic of data-based AI computational approaches is that the computational model is trained on one or more data sources to acquire knowledge.

Considerations for data used in AI systems include acquisition, storage and access.

a) Data acquisition. An AI application's use case and task typically dictate the type of data to be acquired for training. Typical AI system tasks reflected in ISO/IEC 22989 and ISO/IEC 23053 include classification, categorization, (conceptual) clustering, regression, prediction, optimization, NLP (text or speech), perception and system control or behaviour guidance. Depending on the application and task, AI system developers can collect training data through intelligent hardware (e.g. smart bracelet, smart watch, smart phone), IoT sensors (e.g. gravity sensor, temperature sensor, humidity sensor), cameras, microphones or other sensors.

b) Data storage. Collected data are stored in the format and structure consistent with the AI system application and task. Storage approaches and constraints can differ during training and evaluation. In addition, distributed and shared storage can be important data storage considerations.

c) Data access. Rapid access and retrieval of large amounts of data is often necessary in AI systems. Load-balancing techniques are often used to address challenges in data concurrency and network overloading.

In addition to perception-based tasks and applications, cognitive intelligence has become an important aspect of AI systems in which cognitive computing is integrated with industrial knowledge. Using techniques such as NLP and KG, AI systems can reveal implicit knowledge and give insights into relations, logic or patterns that are not easily found by human observers.

EXAMPLE Using KGs, accumulated business process data can be converted into organizational experience and knowledge. This can be used in turn to reduce communication costs among different departments.

6.3.2 Infrastructure-based

AI systems can face simultaneous challenges in computing platform design optimization, computing efficiency in complex heterogeneous environments, highly parallel and scaled computing frameworks, and the computing performance of AI applications. One possible solution to such challenges is to use powerful infrastructures to provide computing capability.

Such infrastructures can include sensor, server, network, processor, storage and other elements. Silicon-based processors are often used for both training and reasoning in learning approaches. When handling large amounts of training data or complex DNN structures, the training processes typically need to execute large-scale calculations on multi-processor systems or processor or accelerator clusters.