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AI-Compass: Functional Paradigm-Based Algorithm Selection Framework

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Abstract

The rapid development of generative AI systems such as ChatGPT has intensified interest in artificial intelligence (AI) across business and industry. Yet, selecting suitable AI algorithms remains challenging, particularly for non-experts facing a complex methodological landscape. This paper introduces the AI-Compass, a structured framework that guides users in selecting appropriate AI algorithms based on functional paradigms (e.g., clustering, anomaly detection, NLP) rather than learning methods. By combining functional classification with paradigm-specific decision diagrams, the AI-Compass offers a transparent, traceable process for algorithm selection. The framework aims to help close the gap between theoretical AI models and industrial practice, enabling data-driven decision-making even for non-specialists.

Keywords
Artificial Intelligence, Algorithm Selection, Industrial Application

1. Introduction

The rapid development and increasing availability of technologies in the field of artificial intelligence (AI) and machine learning (ML) has triggered a profound change in numerous industries in recent years. In particular, the arise of generative AI systems such as ChatGPT has sparked a surge in public and corporate interest in these technologies, not only in an academic context, but also in industrial applications (Chui 2023). While generative AI systems are still in their early stages of practical use in companies, other AI-based applications have already impressively demonstrated the potential of data-driven systems: from increasing efficiency and automating processes to developing innovative business models. Despite this potential, the implementation of AI technologies in practice still faces significant challenges. Companies are not only faced with the question of whether AI is the right solution for a specific problem, but also which algorithm is best suited to meet both, technical requirements and economic objectives. The complexity of the available methodological landscape, the lack of practical selection tools and the shortage of qualified AI specialists further complicate informed decision-making. Although there are numerous scientific publications and technical resources on AI algorithms, these are often fragmented, very abstract or too focused on mathematical-formal content. This creates a significant hurdle for decision-makers without in-depth technological knowledge when identifying suitable solutions (Suh 2021).

The ‘AI-Compass’ in this paper presents a structured decision-making process that offers guidance particularly to managers and staff without in-depth knowledge of AI or Machine Learning. The aim is to enable a comprehensible, systematic selection of suitable AI algorithms tailored to specific problems, the availability of relevant data and the desired results. The ‘AI-Compass’ is based on a comprehensive analysis and categorization of relevant AI methods that are commonly used in industrial applications. This approach is intended to create a practical tool that brings the diversity of AI algorithms into a structured form and thus supports an efficient implementation of AI solutions in companies.

2. State of the Art: Widely used approaches for the selection of AI algorithms

Currently, there are various methods to find a sufficient AI-algorithm for a specific application. The most common approaches are presented below.

2.1 Sorting by learning methods

The common classification of AI algorithms according to learning methods into supervised, unsupervised and reinforcement learning offers a starting point for selecting suitable methods, albeit one that is particularly depending on the availability of data. This classification requires a certain amount of prior knowledge and is insufficient in more complex application scenarios, as it often inadequately reflects hybrid approaches and the specific strengths of individual algorithms (Takyar 2025, Li 2020).

2.2 Automatization of selection

To support algorithm selection, automated approaches have been developed that suggest suitable AI algorithms based on the requirements of a use case. These methods accelerate the selection process and reduce manual effort, required by humans, especially for large amounts of data and clearly defined objectives. However, the lack of transparency of such systems can be problematic, especially in complex or specialised application scenarios, where automated recommendations reach their limits (Kerschke et al. 2018). For instance, automated selection tools in predictive maintenance improved model performance but failed to ensure interpretability (Engbers 2025). Recent work on AutoML and explainable AI emphasize similar goals but remain technology-centric and is therefore not comprehensible to non-experts (Hutter et al. 2019, Molnar 2023).

2.3 Mathematical and logical approach, benchmark-based selection

Another approach to select AI algorithms is systematic evaluation based on mathematical models and benchmark tests. Algorithms are analysed in terms of their performance in standardised tests and in relation to specific mathematical criteria. This method enables an objective and measurable evaluation of the algorithms and helps to compare their performance in different contexts. The main advantage of this approach is the objectivity and measurability of the selection criteria. This allows decisions based on quantitative data, which is useful in both, scientific and industrial applications. However, this approach can lead to excessive focus on benchmarks that do not cover all practical aspects of an application case. It also requires extensive mathematical knowledge and experience to interpret the results. This method is less suitable for applications that need to take qualitative characteristics or user preferences into account and can lead to biased evaluations if contextual factors are not adequately considered. (Gupta and Roughgarden 2015, Meunier 2020, Raschka 2018)

3. Fundamentals of functional paradigms

A key aspect of the functional paradigm methodology is the precise definition and delimitation of the individual paradigms. The functional paradigm strives for a clear and task-oriented classification. It focuses on the questions: "What happens to the processed data and what result is achieved?" and "What function does the algorithm fulfil within the application context?" The definition of paradigms is based on the specific goals and tasks that an algorithm fulfils within a system. Three criteria have proven to be particularly relevant in our context.
First: The objective of data processing. This criterion focuses on the application and the system surrounding the algorithm. It clarifies what function the algorithm fulfils in the application context, what purpose it serves and why a complex algorithm is needed at this point.

Second: The interaction with the environment. The extent to which the algorithm dynamically adapts its decisions to external conditions. This also includes the question of whether an algorithm delivers the same result for the same input data in successive runs. Paradigms such as continuous interaction are relevant, for example, for algorithms that work in real time and in constantly changing environments; working with continuous time series can also be regarded as such an interaction.

Third: The data structure. This criterion differs between the data flow and the structure of the input data (e.g. texts, images, data records) and output data (e.g. class assignment, regression result).

4. Identified functional paradigms

In this chapter, we describe the key functional paradigms that we have identified as representative for common use cases in an industrial context. This categorization creates a practical and task-oriented perspective that differs from traditional learning methods. The selection of the eight paradigms was based on a systematic analysis of industrial use cases. The aim was to reduce the multitude of potential tasks to a manageable number of basic paradigms that cover the range of typical challenges in industrial practice. Other potential paradigms (e.g., time-series forecasting) were considered but classified as subtypes of existing paradigms such as regression or continuous interaction, due to similar methodological principles.

Anomaly detection: An anomaly is a deviation from the expected pattern in data, often relevant in high-dimensional data spaces. In two-dimensional space, this could be a data point that is a certain distance away from all other data points, with these other data points being close together (Figure 1). The primary goal of this paradigm is to identify anomalies during the training phase so that new data points can be classified accordingly later in the inference phase. An alternative application is to make no difference between the training and inference phases and solely to identify anomalies in a data set (Lazarevic et al. 2003).

Clustering: Clustering aims to divide data sets into groups (clusters) so that the data points within a cluster have a higher degree of similarity than data points from different clusters. The criteria for determining similarity vary depending on the algorithm used. Figure 2 shows an example of clusters in two-dimensional space. In practice, however, data with significantly higher dimensions is often processed. Similar to anomaly detection, the focus in training is on forming clusters, while in the inference phase, new data points are assigned to existing clusters. It is also possible to consider only the inference phase and not perform any explicit training. In this case, no new data points can be assigned to the clusters retrospectively (scikit-learn 2025).

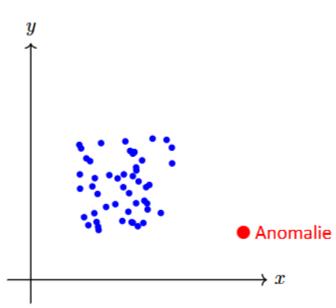

Figure 2. Anomaly in two-dimensional space

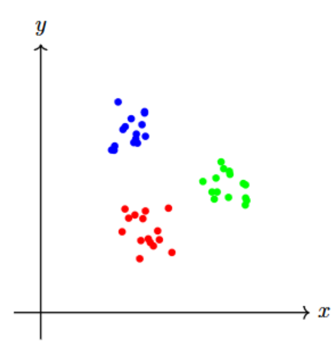

Figure 1 Three Cluster in two-dimensional space

Natural Language Processing: NLP involves the processing of language-based data, where the input and output are usually in text form. This paradigm encompasses the analysis, understanding, and generation of human language through algorithms, it is essential for applications such as translation services, voice assistants, and more (Luong et al. 2015).

Classification: Classification consists of assigning input data to previously defined classes. Depending on the specific algorithm, a probability is also calculated that indicates the degree to which the input data belongs to one, several, or all classes. Classification also includes object recognition, in which parts of the input data, usually in the form of an image, are identified and assigned to a class. Decision-making is also a form of classification, whereby a binary decision is made based on input data (Berrar 2018).

Regression: In contrast to classification, regression generates a continuous value. The main goal of regression is to model and predict data values, whereby a prediction about the output value is made based on the input data (Diaz-Bone 2003).

Continuous Interaction: This paradigm is closely related to reinforcement learning, in which the algorithm operates in a continuous environment. In continuous interaction, a status assessment of the environment is performed, and an action is carried out based on this assessment (Argall et al. 2009).

Image Recognition: The input data for an algorithm is always in a form that can be interpreted as an image. This image-like data does not necessarily have to represent real images but must simply be in a form that can be interpreted as an image. This means that there are usually few dimensions, with the first two describing a position in two-dimensional space and the third dimension describing a color or intensity (Dosovitskiy et al. 2020).

Data processing: In general, all of the paradigms mentioned above can be assigned to the data processing paradigm. In this context, the data processing paradigm functions as a collective category for data that cannot be clearly assigned to any of the other paradigms. The type of this data is either not specified in more detail or it is regarded as binary coded, which basically includes all digital data formats.

5. From Concept to Use: The AI-Compass in Practice

The AI-Compass uses this paradigmatic structure to systematically profile algorithms and to make their typical areas of application understandable. The combination of functional classification with a user-centred presentation creates a tool that offers non-specialists a solid base for decision-making.

5.1 Sorting AI algorithms according to functional paradigms

All considered AI algorithms were cross-sorted according to their functional paradigms (see Figure 3). Algorithms suitable for several paradigms were considered accordingly. The functional paradigm is a fundamental, unchanging property of each application and leads the process for a system to be equipped with an AI algorithm. Hence, this influences all subsequent decisions in the development of an AI system.

	Paradigms							
Algorithms	Anomaly detection	Clustering	Data processing	Natural Language Processing	Classification	Regression	Continuous Interaction	Image Recognition
Local Outline Factor	x							
Expert System	x				x			
Isolation Forest	x							
Fuzzy Clustering		x						
K-Means		x						
Hierarchical Clustering		x						
Autoencoder			x					
Hidden Markov Model			x		x			
Latent Dirchlet Allocation				x				
Long Short-Term Memory				x		x		
Generative Pretrained Transformer				x				
Transformer Architectures				x				
Naives Bayes					x			
Logististic Regression					x			
Random Forest					x	x		
Gradient Boosting Machine					x	x		
Decision Tree					x	x		
K-Nearest Neighbor					x			
Graph Neural Networks					x	x		
Multimodel Parallel Deep Network					x			
Linear or Polynomial regression						x		
Apprenticeship Learning							x	
Q-Learning							x	
Deep Q-Learning							x	
Policy-Gradient Reinforcement Learning							x	
Genetic Algorithms					x		x	
Actor-Critic Reinforcement Learning							x	
Computer Vision without ML			x					x
Support Vector Machines					x			x
Transfer-Learning with CNN								x
Residual Neural Network								x
Convolutional Neural Network								x
Vision Transformer								x

Figure 3. Cross-assignment of algorithms and corresponding paradigms

5.2 Flow charts

Based on this cross-assignment, decision rules are defined and visualised as flowcharts. The paradigm flowchart shown in Figure 4 is used to determine the paradigm suitable for the individual application. Specific decision questions are available for targeted assignment, which enable the correct paradigm to be identified. If the functional paradigm is already known, the paradigm flowchart can be skipped.

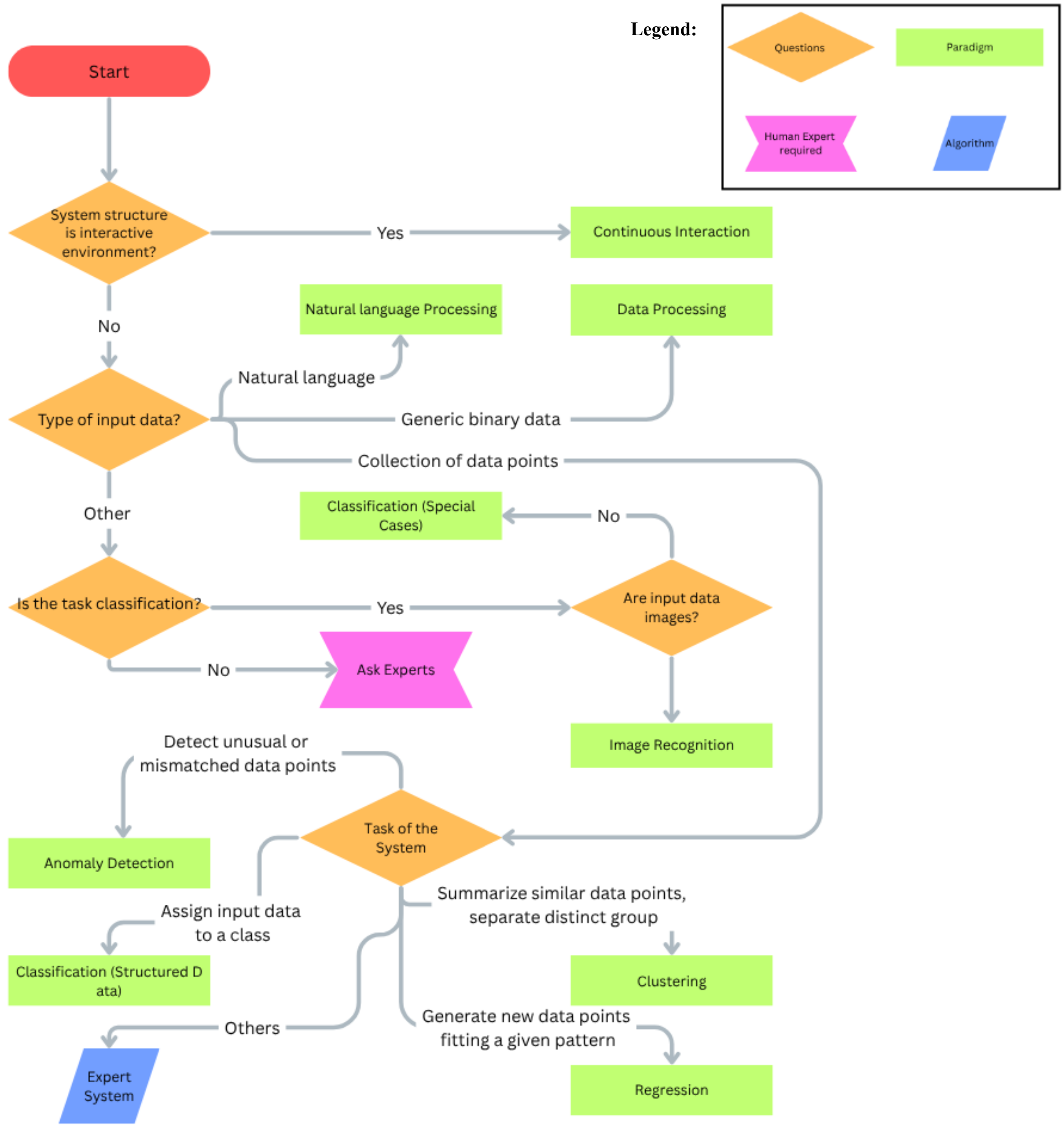

Figure 4. Flowchart for selecting a paradigm

Once the correct paradigm has been determined, the flowchart seen in Figure 5 can then be used to select the appropriate algorithm. The flowchart is described as an example for the 'Clustering' paradigm. The diagram guides users through data-related and analytical criteria such as dataset size, fuzzy membership or visualization needs. It helps users (e.g., in customer segmentation or process grouping) navigate through the algorithm choice.

The decision-making process begins with the question of whether a fuzzy assignment of data points to multiple clusters is necessary. In this case, the use of fuzzy clustering is recommended, as this method allows a data point to belong to multiple clusters with different weights at the same time. This approach is particularly suitable for complex or overlapping structures in the feature space (Ruspini et al. 2019). If fuzzy assignments are not relevant, the size of the data set is included in the decision-making process in the next step. For large data sets, K-means is an efficient clustering method because it offers good scalability with low computational complexity (Ahmed et al. 2020). If so, the use of hierarchical clustering is recommended and results in an intuitive visualization of the hierarchical cluster structure by generating a dendrogram (scikit-learn 2025).

If there are no explicit requirements for visualisability, the choice of method depends on whether the number of clusters to be formed is known in advance. If this information is available, K-means is a suitable method. If the number of clusters is not defined, an additional assessment is conducted to determine whether there are outliers in the data set. In cases where outliers are important, data preprocessing is required before a suitable clustering method can be used. If there are no such outliers, hierarchical clustering can be used as a flexible and robust method. The flowchart shown thus provides a good basis for the methodical selection of clustering methods. It takes into account both, data-related factors (e.g., size, structure, preprocessing requirements) and analytical requirements (e.g., visualization, prior knowledge of the number of clusters).

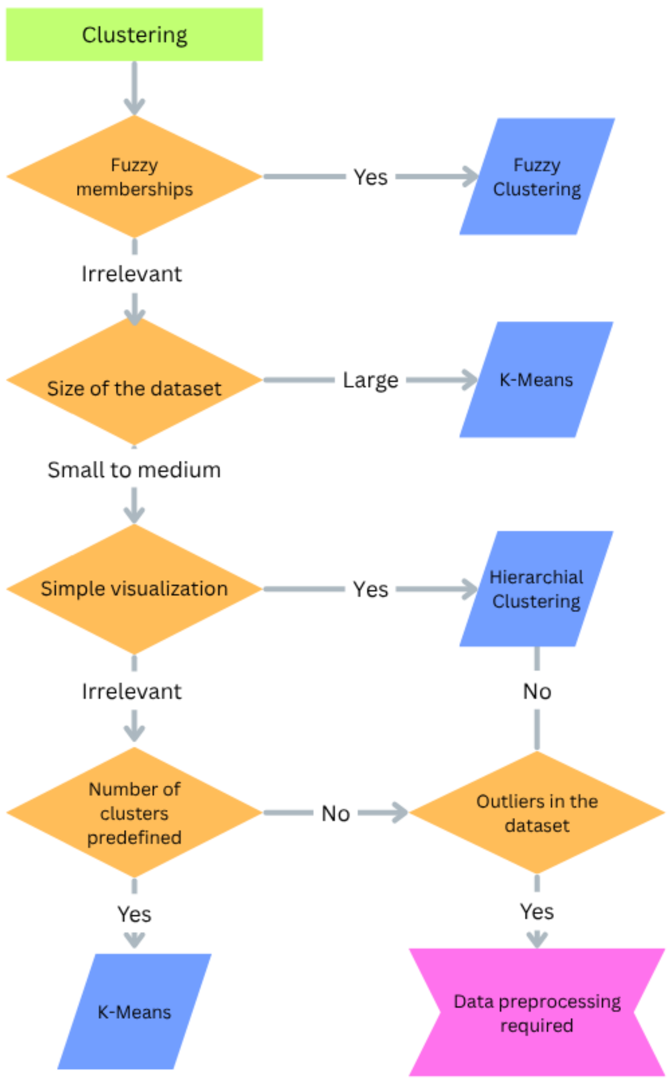

Figure 5. Flowchart for algorithm selection using the clustering paradigm as an example

6. Conclusion
This paper introduced the AI-Compass, a functional-paradigm-based framework designed to support transparent, comprehensible, and methodologically sound AI algorithm selection for industrial applications. By shifting the perspective from traditional learning-method classifications toward task-oriented functional paradigms, the AI-Compass addresses a central gap in current selection approaches: the lack of accessible, problem-centred guidance for non-experts. The framework integrates a systematic categorization of eight functional paradigms with paradigm-specific decision flowcharts, enabling users to translate application characteristics, data structures, and operational constraints into informed algorithmic choices. The evaluation of existing state-of-the-art approaches demonstrated that current methods tend to require specialized knowledge, lack transparency, or remain detached from real-world decision contexts. In contrast, the AI-Compass emphasizes interpretability and applicability by aligning algorithmic functions with industrial problem settings. This functional classification provides a stable conceptual anchor that remains robust across evolving technological developments and hybrid algorithmic designs. The resulting framework is particularly valuable for practitioners in domains where AI expertise is limited but where data-driven decision-making is increasingly essential. Future efforts will focus on integrating the AI Compass into digital decision support systems and testing it in industrial case studies. This will further improve the algorithm selection itself as well as the practical applicability.

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