

# Survey on Data-driven Intelligent Computing and Its Applications

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**Abstract:** In the era of big data with the rapid development of information technology, data presents the characteristics of massive, diverse and high-speed. Traditional computing paradigms face challenges such as low efficiency and poor adaptability when dealing with large-scale, high-dimensional and complex data, and data-driven intelligent computing emerges. With the help of machine learning, deep learning and other technologies, this computing mode can automatically learn knowledge and build models from data to realize intelligent analysis and decision-making of complex problems. Intelligent computing models include supervised learning, unsupervised learning and reinforcement learning. In practical applications, image recognition and computer vision, natural language processing, intelligent recommendation systems and other fields have achieved remarkable results, but they also face challenges such as data quality, model interpretability, computing resource requirements, and privacy security. Data-driven intelligent computing will develop in the direction of integration with knowledge graph, edge computing, cloud computing, and cross-domain application expansion, and continue to promote the intelligent process in various fields.

**Keywords:** Data-driven; Intelligent Computing; Machine Learning; Deep Learning.

## 1. Introduction

Intelligent computing has powerful self-learning ability, which can continuously adjust its parameters and structure to adapt to different tasks and environments by learning from large amounts of data. Intelligent computing also has the characteristics of self-organization and self-adaptation. In the face of complex and changeable problems and environments, intelligent computing systems can automatically organize their structures and functions to better adapt to changes. Data-driven intelligent computing opens up entirely new research directions and perspectives for computer science and related disciplines [1]. It breaks the limitations of traditional computing paradigms and promotes theoretical innovation and development in machine learning, deep learning, artificial intelligence and other fields.

In order to cope with the challenges of the era of big data and fully tap the value of big data, data-driven intelligent computing comes into being. Data-driven intelligent computing takes data as the core. With the help of advanced technologies such as machine learning, deep learning and artificial intelligence, it can automatically learn and extract knowledge from large amounts of data, build intelligent models, and realize intelligent analysis and decision-making of complex problems [2, 3]. Different from the traditional computing paradigm, data-driven intelligent computing pays more attention to the driving role of data. Through deep mining and analysis of data, hidden patterns and rules are found in the data, so as to realize a more accurate understanding and solution to the problem. The basic idea is to automatically learn and extract knowledge from a large amount of data, and use the information contained in the data to guide decision-making and model construction [4]. In data-driven intelligent computing, data is not only the input of the calculation, but also the key factor that drives the whole calculation process and determines the calculation result.

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adapt to different tasks and environments by learning from large amounts of data. Intelligent computing also has the characteristics of self-organization and self-adaptation. In the face of complex and changeable problems and environments, intelligent computing systems can automatically organize their structures and functions to better adapt to changes. Data-driven intelligent computing opens up entirely new research directions and perspectives for computer science and related disciplines. It breaks the limitations of traditional computing paradigms and promotes theoretical innovation and development in machine learning, deep learning, artificial intelligence and other fields [5, 6]. Through the research of data-driven intelligent computing, scholars can deeply explore how to automatically learn and extract knowledge from massive and complex data, and build more intelligent and efficient models and algorithms, which not only enriches the theoretical system of intelligent computing, but also provides new methods and tools for the research of other disciplines.

## 2. Related Work

In the field of data-driven intelligent computing, scholars and research institutions both at home and abroad have conducted extensive and in-depth research, achieving a series of results with significant theoretical and practical value.

The landscape of data-driven intelligent computing encompasses a broad spectrum of emerging technologies and applications, as reflected in recent comprehensive surveys. Wu et al. [7] provided an overarching view of digital twin networks, emphasizing their role in creating dynamic, real-time virtual representations of physical systems, which are fundamental to intelligent computing frameworks. This concept underpins many applications where real-time data processing and simulation are critical.

Deep learning and reinforcement learning techniques are central to advancing intelligent computing. Chen et al. [8] survey the deployment of Deep Reinforcement Learning (DRL) in IoT environments, discussing how DRL algorithms

enable autonomous decision-making and adaptive control in complex systems. Similarly, Jin et al. [9] focus on spatio-temporal graph neural networks (STGNN), which are instrumental in predictive learning for urban computing, supporting applications like traffic forecasting and environmental monitoring.

Edge intelligence (EI) emerges as a pivotal approach for deploying intelligent computing at the network edge, reducing latency and bandwidth demands. Amin et al. [10] analyze edge architectures in healthcare, emphasizing AI-based classification and prediction techniques that facilitate real-time decision-making in critical scenarios.

Gong et al. [11] further elaborate on the application of EI in ITS, identifying challenges and demonstrating how EI can empower transportation systems through localized data processing. The management of network resources through intelligent slicing is another significant aspect. Wu et al. [12] review intelligent network slicing management in industrial IoT, illustrating how integrated approaches can optimize service delivery across smart transportation, energy, and manufacturing sectors.

Furthermore, the application of data-driven intelligence extends to public health and social systems. Roy et al. [13] survey pandemic management architectures, emphasizing the role of data repositories and contact-tracing applications in controlling disease spread. Similarly, Lv et al. [14] explore behavioral modeling and prediction, providing insights into social perception and the development of smart social systems within urban environments.

In summary, these surveys collectively depict a rapidly evolving field where data-driven intelligent computing is applied across diverse domains, including transportation, healthcare, urban management, and public safety. The integration of advanced algorithms, edge computing, and network management strategies is central to realizing the full potential of intelligent systems in a data-centric era.

### 3. Intelligent Computing Model and Method

#### 3.1. Supervised Learning

Supervised learning is an important branch of machine learning and plays a key role in data-driven intelligent computing. Its core feature is that it uses labeled training data to train the model, and constructs a model that can predict unknown data by learning the mapping relationship between the input data and the corresponding label. In a regression task, the loss function can be mean squared error (MSE), which measures the prediction error of a model by calculating the average of the sum of squared errors between the predicted and true values of the model. During the training process, the model will constantly adjust its parameters to minimize the MSE and thus improve the accuracy of the prediction.

##### 3.1.1. Linear Models

Linear model is a kind of basic and important model in supervised learning, which predicts by linear combination of input features. It has the advantages of simple form and strong interpretability, and is widely used in many fields.

Linear regression is a classic linear model used to predict continuous values. The basic principle is to find the best linear function that fits the data by minimizing the sum of squared errors between the predicted and true values. In the house price prediction, it is assumed that the house price is affected by the house area, the number of rooms, and the age of the

house. We can use these factors as input features and house prices as output labels. A linear regression model tries to find a set of coefficients (weights) that minimize the sum of squared errors between the predicted home price and the true home price as a linear combination of these features. The linear regression model formula can be expressed as follows.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \delta \quad (1)$$

Here  $y$  is the predicted house price,  $x_1, x_2, \cdots, x_n$  is the input feature,  $\beta_0, \beta_1, \beta_2, \cdots, \beta_n$  is the coefficient of the model, and  $\delta$  is the error term. In practice, the least squares method is usually used to solve these coefficients to find the best fitting line. By learning and training a large number of house data, the linear regression model can predict the corresponding house price according to new house characteristics.

Logistic regression is actually a linear model for binary classification problems. The principle is to achieve classification by transforming the output of linear regression through the Sigmoid function to map the output value to a probability value between 0 and 1. The expression for the Sigmoid function is

$$\sigma(z) = \frac{1}{1 + e^{-z}} \quad (2)$$

Here  $z$  is the output of linear regression. The logistic regression model first results in a linear score  $z$  by linearly combining these features, which is then fed into the Sigmoid function to obtain a probability value between 0 and 1. Usually, 0.5 is used as the threshold. During training, the model continuously adjusts the parameters such that the probability of correct prediction is maximized for known training data.

Linear models are of great value in practical applications, but they also have some limitations. Linear models assume that there is a linear relationship between input features and output. For some complex nonlinear problems, linear models have limited fitting ability and may not accurately capture complex patterns and laws in the data. Linear models are still the model of choice in many practical applications due to their simplicity, computational efficiency and interpretability, and when combined with other techniques, they can also overcome their limitations to some extent and play a greater role.

##### 3.1.2. Nonlinear Model

Nonlinear models play an important role in intelligent computing. They can deal with the complex nonlinear relationship between input and output, make up for the shortcomings of linear models, and show powerful capabilities and wide applications in many fields such as image recognition and text classification.

Decision tree is a typical nonlinear model, which makes decision and classification by building a tree structure. The building process of the decision tree is based on the recursive partitioning of the data set, and the optimal feature is selected at each node to split, so that the divided child data set is cleaner in terms of categories. The advantages of decision trees are that the model is simple and intuitive, easy to understand and explain, can handle both discrete and continuous data, and does not require complex data preprocessing. However, decision trees are prone to overfitting, especially when the dataset is small or has many features. In order to overcome the overfitting problem,

pruning techniques are usually used to simplify the decision tree, remove some unnecessary branches, and improve the generalization ability of the model.

Support Vector Machine (SVM) is also a commonly used nonlinear model. Its core idea is to find an optimal hyperplane to separate the data points of different classes as much as possible, and maximize the margin between the two classes of data points and the hyperplane. For linearly separable data, SVM can directly find such hyperplanes. SVM performs well in dealing with high-dimensional data and small sample data, with high classification accuracy and good generalization performance. However, the computational complexity of SVM is high, especially when dealing with large-scale data sets, the training time is long, and it is sensitive to the choice of kernel function and parameter adjustment, which requires some experience and skills.

## 3.2. Unsupervised Learning

As an important branch of machine learning, unsupervised learning has a unique position and role in data-driven intelligent computing. It aims to automatically discover potential patterns, structures and regularities from the data, and mine the intrinsic characteristics and information of the data. The main tasks of unsupervised learning include clustering, dimensionality reduction, anomaly detection, etc.

### 3.2.1. Clustering Algorithms

Clustering algorithm is an important algorithm in unsupervised learning. Its core goal is to divide the samples in the data set into different clusters according to their similarity, so that the samples in the same cluster have high similarity, and the samples between different clusters have large differences.

K-Means algorithm is a classical clustering algorithm, which has the advantages of simple principle and high computational efficiency. The basic idea is to first randomly select an initial cluster center, then calculate the distance from each sample to the center, and assign the sample to the cluster with the closest center. Next, the center of each cluster is recalculated. Typically, the new center is calculated as the mean of all the samples in the cluster. This process is repeated until the cluster centers do not change or a preset number of iterations is reached.

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm is a density-based clustering algorithm. Unlike K-Means algorithm, it does not need to specify the number of clusters in advance. It can find clusters of arbitrary shape and identify noise points in the data set. The principle of DBSCAN algorithm is based on the density of data points, if the density of data points in a region exceeds a certain threshold, the points are divided into a cluster.

Clustering algorithms have achieved remarkable results in practical applications, but they also face some challenges. Different clustering algorithms have different requirements for the distribution and characteristics of the data, and choosing the appropriate clustering algorithm and parameters is a complex problem that needs to be experimented and tuned according to the specific data and application scenarios. The evaluation of clustering results is also a difficulty, since there are no pre-labeled labels, it is difficult to objectively evaluate the quality and effect of clustering.

### 3.2.2. Dimensionality Reduction Algorithms

In data-driven intelligent computing, the processing of high-dimensional data is a key problem. High-dimensional

data not only increases the computational complexity, but also may lead to the curse of dimensionality, making the training and analysis of models difficult. The purpose of dimensionality reduction algorithm is to transform high-dimensional data into low-dimensional data while preserving the main characteristics and information of the data.

Principal Component Analysis (PCA) is a widely used linear dimensionality reduction algorithm. It projects the original data into a new low-dimensional space by linear transformation, so that the projected data has the largest variance. The basic principle of PCA is based on the covariance matrix of the data, and through the eigen decomposition of the covariance matrix, the eigenvalues and eigenvectors are obtained. The eigenvalues represent the variance of the data in the direction of the eigenvectors, which represent the direction of the projection. The feature values are sorted from large to small, the feature vectors corresponding to the top  $k$  largest feature values are selected, and the original data is projected into the new space composed of these  $k$  feature vectors to achieve dimensionality reduction.

t-SNE (t-Distributed Stochastic Neighbor Embedding) is a nonlinear dimensionality reduction algorithm, which is suitable for visualization of high-dimensional data. Different from PCA, t-SNE can better preserve the local structure and similarity of the data in the high-dimensional space. The principle of t-SNE is to map data points in the high-dimensional space to the low-dimensional space by constructing a probability distribution, such that data points that are similar in the high-dimensional space are also similar in the low-dimensional space.

Linear dimensionality reduction algorithms such as PCA have limited processing ability for nonlinear data, and may not accurately preserve the characteristics and structure of the data. Although nonlinear dimensionality reduction algorithms such as t-SNE can better deal with nonlinear data, they have high computational complexity and long computing time, and the dimensionality reduction results may have some randomness.

## 3.3. Reinforcement Learning

Reinforcement learning is an important field of machine learning. It focuses on how an Agent can learn an optimal behavior policy by interacting with the environment in a dynamic environment with the goal of maximizing the cumulative reward.

Reinforcement learning mainly consists of several key elements: agent, environment, state, action and reward. Agents are entities that perform actions and learn from their environment; The environment is the external world of the agent, which generates new states and reward feedback based on the agent's actions. The state is a description of the current situation of the environment, which contains the information that the agent needs to make a decision. Actions are the actions that an agent can take in a state; The reward is the environment's feedback to the agent after taking an action. It indicates how good or bad the action was.

Q learning is a classical reinforcement learning algorithm, which belongs to the model-free learning method. The  $Q$  represents the expectation of the cumulative reward that can be obtained by taking an action in a state. The core idea of Q learning is to use the Bellman equation to update the  $Q$  value and gradually approach the optimal  $Q$  value function. The basic form of the Bellman equation is:

$$Q(s, a) = Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)] \quad (3)$$

Where  $Q(s, a)$  is the  $Q$  value for taking action  $a$  in the current state  $s$ ,  $\alpha$  is the learning rate, which controls the step size for each update,  $r$  is the reward obtained after taking action  $a$ ,  $\gamma$  is the discount factor, which measures the importance of future rewards and ranges from 0 to 1.  $s'$  is the new state to transition to after taking action  $a$ , and  $\max_{a'} Q(s', a')$  represents the maximum q-value that can be obtained in the new state  $s'$ .

Deep Q-Network (DQN) is developed on the basis of Q-learning. It introduces a deep neural network to approximate the Q-value function, which solves the problem that the Q-value table is too large to store and calculate when dealing with high-dimensional state space in traditional Q-learning. DQN uses a neural network instead of a Q-value table, taking the state as input to the neural network and outputting the Q-value for each action. DQN also introduces two important techniques, experience replay and target network. Experience replay is to store each step of the agent's interaction in the environment into the experience pool, and then randomly sample a batch of data from the experience pool for training during training, which can break the correlation between the data and improve the stability of training. The target network is a network with the same structure as the main network but with a slower parameter update, which is used to calculate the target Q value and reduce the oscillations during training.

## 4. Typical Applications in the Computer Field

### 4.1. Image Recognition and Computer Vision

Image recognition and computer vision are important application directions of data-driven intelligent computing in the computer field. They are committed to enabling computers to understand and parse image content, and play a key role in many fields.

In the field of security monitoring, image recognition technology is widely used in face recognition, behavior analysis and object detection. Face recognition technology realizes the identification and verification of personnel by extracting and comparing the features of faces in surveillance videos. Public security organs can use face recognition system to quickly identify criminal suspects and improve the efficiency of solving cases. Behavior analysis analyzes the behavior of the personnel in the surveillance video, such as detecting abnormal behavior, crowd density monitoring, etc., to find security risks in time.

Medical image analysis is an important application of image recognition and computer vision in the medical field. Through the analysis of X-ray, CT, MRI and other medical images, computers can assist doctors in disease diagnosis. In X-ray image analysis, image recognition technology can detect lung lesions, such as pneumonia, tuberculosis, lung cancer, etc. Through the feature extraction and analysis of X-ray images, the computer can identify abnormal shadows, nodules and other lesions in the lung, and provide diagnostic reference for doctors. CT image analysis can observe the internal structure of the human body in more detail, which is of great significance for the diagnosis of brain diseases, chest diseases and abdominal diseases. MRI image analysis plays

an important role in the diagnosis of nervous system diseases and joint diseases.

Despite the remarkable achievements in practical applications of image recognition and computer vision, there are still many challenges. Data quality has a crucial impact on model performance, and high-quality labeled data is the basis for training accurate models. However, obtaining a large amount of high-quality labeled data is often costly, and the labeling process is prone to errors. In medical image annotation, professional doctors are needed for annotation, which is not only time-consuming and laborious, but also different annotations from different doctors may exist. The generalization ability of the model is also a key issue. Current image recognition models perform well on specific data sets, but when facing images in different scenes and under different conditions, their generalization ability is insufficient and they are prone to misjudgment.

In the future, image recognition and computer vision technology will develop in the direction of higher accuracy, stronger generalization ability and better real-time performance. With the continuous development of deep learning technology, new network architectures and algorithms will constantly emerge, which are expected to further improve the accuracy and performance of image recognition.

### 4.2. Natural Language Processing

Natural language processing is another important application field of data-driven intelligent computing in the computer field. It is dedicated to making computers understand and generate human language and realize natural interaction between human and computer. With the increasing amount of data and the continuous progress of intelligent computing technology, natural language processing has made significant progress in intelligent customer service, machine translation, text generation and so on.

Machine translation is an important application direction of natural language processing, which aims to realize automatic translation between different languages. In recent years, neural network based machine translation technology has made a great breakthrough, significantly improving the quality and efficiency of translation. In international business communication, when enterprises communicate with foreign customers by email, machine translation can help both sides quickly understand each other's language content and promote the smooth progress of business cooperation. Despite the great progress made in machine translation, there is still a problem of insufficient accuracy when dealing with texts in some specialized fields [15]. Terms and language expressions in professional fields have strong professionalism and uniqueness, and machine translation may not be able to accurately understand and translate these contents.

By analyzing and understanding the text input by the user, intelligent customer service can automatically identify the user's questions and intentions, and provide accurate answers and solutions. The intelligent customer service system of some e-commerce platforms can quickly respond to users' inquiries and answer questions about product information, order status, and after-sales service by using natural language processing technology. When a user asks, "When will my purchase ship?" The intelligent customer service system can

query the order system through the understanding of the problem, and reply to the user's estimated delivery time in time.

However, intelligent customer service still has some limitations in dealing with complex semantics and context understanding. When the user's question is vague or ambiguous, intelligent customer service may not accurately understand the user's intention, resulting in inaccurate answers or unable to provide effective solutions. For some problems involving emotion and subjective judgment, the processing ability of intelligent customer service also needs to be improved. In order to break through these bottlenecks, researchers are exploring more advanced semantic understanding technologies, such as the semantic representation model based on deep learning, combined with knowledge graph and other technologies, to enhance the ability of intelligent customer service to understand the context and semantics, and improve the accuracy and intelligence of the answer.

### 4.3. Intelligent Recommender Systems

As a typical application of data-driven intelligent computing, intelligent recommendation system plays an important role in e-commerce, music, news and other fields. Through in-depth analysis of user data, it provides users with personalized recommendation services to improve user experience and business efficiency.

In the field of e-commerce, intelligent recommendation systems are widely used. By collecting users' browsing history, purchase records, search keywords and other multi-dimensional data, collaborative filtering, content-based recommendation and other algorithms are used to accurately recommend products for users. When a user browses a laptop, the system will recommend relevant accessories, such as laptop bags, mice, keyboard membranes, etc., according to the purchase history of other users with similar browsing and purchasing behavior. At the same time, it will also recommend other laptops with the same brand or price to meet different needs of users.

In order to improve the recommendation accuracy and diversity of intelligent recommender systems, researchers and engineers continue to explore and improve methods. In terms of algorithms, it is an effective way to integrate multiple recommendation algorithms. Collaborative filtering algorithm can find the similarity between users, and content-based recommendation algorithm can make recommendations according to the characteristics of items [16]. The collaborative filtering algorithm can be used to find out the user group with similar interests to the target user, and then from these users' favorite items, the items that are similar to the historical preference content of the target user can be selected for recommendation.

In terms of data processing, enriching data sources and improving data quality are key. In addition to the user's behavior data, it can also collect the user's social data, demographic data, etc., to fully understand the user's interests and needs from multiple dimensions. In the evaluation and optimization of recommendation results, a scientific evaluation index system is established, such as accuracy, recall, F1 score, Mean Absolute Error (MAE) and so on. According to the evaluation results, the parameters and strategies of the recommendation algorithm are adjusted in time, and the recommendation model is optimized to improve the accuracy and diversity of the recommendation. The user

feedback mechanism can also be used to let users evaluate and feedback the recommendation results. According to the user's feedback, the recommendation system can be constantly improved to meet the personalized needs of users.

## 5. Summary

This paper presents a comprehensive and in-depth discussion on data-driven intelligent computing and its applications, covering basic theories, key technologies and typical applications, and has achieved a series of valuable research results. Data quality is one of the fundamental challenges in data-driven intelligent computing. The data sources in the real world are wide and complex, and there are often problems such as data missing, noise, and inconsistency. With the wide application of complex models such as deep learning in intelligent computing, the interpretability of models is becoming worse and worse. Deep learning models are usually composed of multiple hidden layers, and their internal decision-making process is like a "black box", which is difficult to be understood and explained by humans. Intelligent computing models, especially deep learning models, have a huge demand for computing resources.

A large amount of data is collected, stored and used, which contains sensitive information of many users, such as personal identity information, health data, financial data, etc. If these data are leaked or misused, it will cause serious damage to the privacy and rights of users. Some enterprises may excessively collect user data and use it for commercial purposes, violating users' privacy rights. How to protect data privacy and security, prevent data leakage and abuse, and improve the security and robustness of intelligent computing models are the key issues to be solved urgently.

Looking forward to the future, the research of data-driven intelligent computing has a broad development prospect, and many frontier directions need to be explored. At the level of theoretical research, the theoretical foundation of machine learning and deep learning still needs to be further consolidated. Explore the cross integration of machine learning and deep learning with other disciplines, to open up new research fields and methods.

## Competing Interests

The authors declare that they have no competing of interest.

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