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СОВРЕМЕННЫЕ ТЕНДЕНЦИИ В КОМПЬЮТЕРНОМ АНАЛИЗЕ ДАННЫХ

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Аннотация. Описываются современные тенденции в компьютерном анализе данных, представленные на конференции «Компьютерный анализ данных и моделирование» и конгрессе «Информационные системы и технологии».

Ключевые слова: статистический анализ данных; робастность; стохастика; дискретные данные; нейронные сети; компьютерное зрение.

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CURRENT TRENDS IN COMPUTER DATA ANALYSIS

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Abstract. The current trends in computer data analysis presented at the conference «Computer data analysis and modelling: stochastics and data science» and the congress «Information systems and technologies» are described.

Keywords: statistical data analysis; robustness; stochastics; count data; neural networks; computer vision.

Introduction

The special issue «Stochastics and data science» of the publication «Journal of Belarusian State University. Mathematics and Informatics» is based on extended papers presented at the 14th International scientific conference «Computer data analysis and modelling: stochastics and data science» and the 11th International congress on computer science «Information systems and technologies», which were held in 2025 in Minsk. All articles underwent the double-blind peer review process standard for the journal.

The structure of this paper is as follows: sections «International scientific conference "Computer data analysis and modelling"» and «International congress on computer science "Information systems and technologies"» are devoted to short description of the indicated conference and congress; sections «Current trends in statistical data analysis» and «Current trends in data science» are presented our version of current trends in computer data analysis and in data science, respectively; section «Short description of the contributed papers» presents short descriptions of the contributed papers.

International scientific conference «Computer data analysis and modelling»

International scientific conference «Computer data analysis and modelling» (CDAM) has been held regularly (every two or three years) since 1988. This conference was held in September 1988, December 1990, December 1992, September 1995, June 1998, September 2001, September 2004, September 2007, September 2010, September 2013, September 2016, September 2019, September 2022 and September 2025 in Minsk.

The CDAM conference is currently the largest scientific forum on statistical data analysis in the post-Soviet area attracting significant interest both in Belarus and the CIS countries, as well as in countries further abroad. Nowadays the conference is included into the list of conferences of the International Institute of Mathematical Statistics. The goal of the CDAM conference is to organise a broad scientific forum for researchers from various countries to discuss and to exchange the latest scientific results in the field of data analysis theory, statistical modelling, statistical software, as well as their applications in scientific research, economics, information security, medicine and in other areas.

This conference is organised by the Belarusian State University (BSU), the Research Institute for Applied Problems of Mathematics and Informatics of BSU, Lomonosov Moscow State University and the Vienna University of Technology. Traditionally, the conferences are held with the financial support of the Ministry of Education of the Republic of Belarus, the Belarusian Republican Foundation for Fundamental Research and the Scientific and Technological Association «Infopark». Holding such a forum at BSU is not random. BSU is the country's leading scientific centre in a set of priority research areas related to the development and use of new information technologies. This includes computer data analysis and modelling of complex stochastic systems in various fields: scientific research, digital economy, manufacturing, information security, medicine, banking, business and other. Also, the faculty of applied mathematics and computer science of BSU trains bachelor's degree specialists to work in these fields under the following programmes: applied mathematics, computer science, applied informatics and computer security. Additionally, the master's programme in computer data analysis is offered.

The previous conference in 2022 was attended by over 100 scientists and young researchers from Austria, Belarus, Germany, Italy, Kazakhstan, Russia, the USA, Uzbekistan, the Czech Republic and Luxembourg. The programme and organising committee members were leading experts in the field of robust and computer methods of data analysis and stochastic systems modelling from seven countries.

The theme of the CDAM conference that held in 2025 is «Stochastics and data analysis» (fig. 1). It combines fundamental science, namely mathematical statistics as the theoretical foundation of data science, with relevant applied research. This theme encompasses mathematical models, methods, algorithms and software for data analysis and stochastic modelling. The goal is to obtain optimal statistical inferences (decisions, estimates, forecasts), as well as to develop computer models of complex stochastic systems and processes. This area is classified among the priority research directions approved by the Council of Ministers of the Republic of Belarus.

Fig. 1. Participants of the CDAM conference that held in 2025

The conference significance is also underscored by the participation of young scientists, master's degree students, postgraduate students and undergraduate students. As it is well known, the majority of winners of various-level school, university and international olympiads in mathematics and computer science successfully study at the faculty of applied mathematics and computer science of BSU. Starting from their 1st or 2nd year, they are engaged in research within student scientific clubs, student research laboratories and the Research Institute for Applied Problems of Mathematics and Informatics of BSU.

Examples of important applied achievements by Belarusian scientists include:

• development and testing of computer systems for information security in the banking sector of the Republic of Belarus;

• creation of econometric models and leading economic indicators for analysing and forecasting the dynamics of key macroeconomic and monetary indicators, as well as algorithms and software for the statistical analysis of the economic creditworthiness and the stability of the banking system at macro and micro levels;

• development of statistical methods and instrumental tools for solving applied problems in medicine for the N. N. Aleksandrov National Cancer Centre of Belarus, the Scientific and Practical Centre «Cardiology» and the department of medical radiology of the Ministry of Health of the Republic of Belarus.

International congress on computer science «Information systems and technologies»

Since 2002, BSU organised and began hosting the International scientific conference «Information systems and technologies». This conference was held every two years (2002, 2004, 2006, 2008, 2009, 2011, 2013, 2016, 2020 and 2022). It has become the International congress on computer science «Information systems and technologies» (CSIST) since 2011. The ideologist and main organiser of the conference throughout its existence was the dean of the faculty of applied mathematics and informatics of BSU P. A. Mandrik, and the faculty of applied mathematics and informatics of BSU served as its venue. CSIST is a large-scale and significant forum in the information technologies field. It aims to exchange experiences among the global scientific community, accumulate ideas and new solutions in information security and develop effective responses to modern challenges.

Let us note that CSIST that held in 2025 took place in 29–31 October 2025 in Minsk (fig. 2). The forum was organised by BSU and the United Institute of Informatics Problems of the National Academy of Sciences of Belarus. Over 200 scientists from Azerbaijan, Belarus, Kazakhstan, China, Portugal, Russia, Serbia, Turkey and Switzerland participated in the congress. It was opened on 30 October at BSU with a plenary session, featuring the most significant presentations by leading scientists. In particular, experts discussed computer vision (CV) in multimodal artificial intelligence (AI) systems, the use of deep learning to classify sleep stages and the development of an intelligent system for analysing patient medical data. The researchers also presented data from an analysis of human behaviour, when interacting with virtual environments, discussed topics such as teacher training in the context of digital transformation, challenges of higher education during the information technology revolution and more.

Fig. 2. Opening ceremony of the CSIST that held in 2025

A total of 174 papers were submitted for the CSIST, and 124 articles were accepted for publication. The congress proceedings were published in two parts and comprise nearly 1 thsd pages. The number of paper authors was 237, including 35 doctors of science and 78 PhD.

Current trends in statistical data analysis

Robustness in statistical data analysis. The final result of statistical data analysis is a statistical inference (estimate, forecast, decision, etc.) based on some observed (registered) statistical data X. Respectively, statistical data analysis consists of different branches: statistical estimation, statistical forecasting (prediction), statistical classification (pattern recognition), etc. To be more precise let us describe the current trend «robustness» in connection with forecasting of future states in time series.

The mathematical substance of the statistical forecasting problem is quite simple – to estimate the future value $x_{T+\tau} \in \mathbb{R}^d$ of the d-variate time series in $\tau \in \mathbb{N}$ steps ahead by successive observations $X = \left(x_1, x_2, \ldots, x_T\right) \in \mathbb{R}^{Td}$. In practice it was detected by many researchers that the optimal forecasting algorithms on the real statistical data have the risk values that are much more than the expected theoretical values. In lecture at the International congress of mathematicians P. Huber explained the reason of this strange situation as follows: «Statistical inferences (including statistical forecasts) depend only in part upon the observations. An equally important base is formed by prior assumptions about the underlying situation». The system of prior assumptions is called the hypothetical model of the data M_0. In applied problems the hypothetical model assumptions M_0 are often distorted, and this fact leads to the instability of the optimal forecasting statistics that are optimal only under M_0.

The probability model of the observed time series under distortions is determined by the family of probability distributions $\left\{P_T^{\varepsilon}\left(X\right) : X \in \mathbb{R}^{Td} : T \in \mathbb{N},\ \varepsilon \in \left[0, \varepsilon_+\right]\right\}$, where ε is the distortion level; $\varepsilon_+ \geq 0$ is its maximal admissible value. If $\varepsilon_+ = 0$, then the distortions are absent, and we have the hypothetical model M_0. A classification scheme for typical distortions of hypothetical models is given in work [1].

Let $\hat{x}_{T+\tau} = f\left(X\right) : \mathbb{R}^{Td} \to \mathbb{R}^d$ be any forecasting statistic. Its performance is evaluated by the mean square risk of forecasting

$$r_{\varepsilon} = r_{\varepsilon}\left(f\right) = \mathbb{E}_{\varepsilon}\left\{\left\| \hat{x}_{T+\tau} - x_{T+\tau} \right\|^2\right\} \geq 0,\ \varepsilon \in \left[0, \varepsilon_+\right],$$

where $\mathbb{E}_{\varepsilon}\left\{\cdot\right\}$ is the expectation symbol with reference to the probability distribution $P_T^{\varepsilon}\left(\cdot\right)$. If the distortions are absent ($\varepsilon = 0$) and the hypothetical model M_0 is valid, this functional is called the hypothetical risk $r_0 = r_0\left(f\right)$. The guaranteed (upper) risk is

$$r_+ = r_+\left(f\right) = \sup_{0 \leq \varepsilon \leq \varepsilon_+} r_{\varepsilon}\left(f\right),$$

where the supremum is taken on all admissible distortions of the hypothetical model M_0. Let $\hat{x}^0_{T+\tau} = f^0\left(X\right)$ be the optimal forecasting statistic under the known hypothetical model M_0 ($\varepsilon = 0$) that gives the minimal value to the hypothetical risk

$$r_0 = r_0\left(f^0\right) = \inf_{f(\cdot)} r_0\left(f\right).$$

The risk instability coefficient k is the relative increment of the guaranteed risk with reference to the minimal hypothetical risk:

$$k = k(f) = \frac{r_+(f) - r_0}{r_0 \geq 0}.$$

For any $\delta > 0$ define a characteristic of robustness that is called the δ-admissible distortion level and is quite useful in applications:

$$\varepsilon^* = \varepsilon^*(\delta) = \sup\{\varepsilon \in [0, \varepsilon_+] : k(f) \leq \delta\}.$$

It indicates the maximal level of distortions for which the relative increment of the risk is yet not greater than the fixed value $\delta \cdot 100$ %.

The smaller the value of k and the greater the value of ε^*, the more robust the forecasting statistic. The minimax robust forecasting statistic $\hat{x}^*_{T+\tau} = f^*(X)$ minimises the risk instability coefficient:

$$k(f^*) = \inf_{f(\cdot)} k(f).$$

Further expansion of robustness paradigm in statistical forecasting is possible in two main directions [1–9]: 1) using new distortion types for the underlying hypothetical model of observed data; 2) using new more complex hypothetical models.

Considering the first direction, let us indicate some distortion types that are topical for practice:

• presence of incomplete data including, namely missing values (when a portion of d_t, $1 \leq d_t \leq d$, components of x_t at the time point t is not observed), censoring (when at the time point t not exact value x_t but only an event $\{x_t \in A_t\}$, $A_t \subset \mathbb{R}^d$, concerning x_t is observed); e. g. $A_t = \{x_{t,1} > c\}$, where $c \in \mathbb{R}^1$ is some known threshold;

• simultaneous (joint) influence of several distortion types on the underlying hypothetical model, e. g. simultaneous influence of outliers and jointly missing values are present.

Concerning the second direction in the development of robust forecasting, let us mention some complex (non-conventional) hypothetical probabilistic models actively used in data analysis:

• multivariate discrete-valued time series $x_t = (x_{t,i}) \in V^d$, where V is some discrete set of cardinality $2 \leq |V| \leq +\infty$ (this model is extremely helpful in many applied areas, e. g. in genetics ($d = 1$, $|V| = 4$), information protection ($d = 64$, $|V| = 2$));

• spatial or spatio-temporal data (random fields) $x_t \in V^d$, where $t = (t_j) \in \mathbb{R}^N$ is an N-dimensional parameter indicating spatial or jointly spatial and temporal coordinates of an observation x_t, e. g. images, meteorological maps, dynamical maps of incidence rates.

Statistical analysis of discrete-valued time series. In any digitised society a multitude of discrete-valued data is generated. If these discrete-valued data are considered dynamically (as dependent on discrete time $t \in \mathbb{Z}$), we obtain a discrete-valued time series $x_t \in \mathrm{A}$, where A is a discrete set. In particular, if $\mathrm{A} = \{0, \ldots, N-1\}$, $N = |\mathrm{A}|$, $2 \leq N \leq +\infty$, we obtain a count time series.

The theory of statistical analysis of time series is deeply developed only for the so-called continuous time series, where A is a subset of $\mathbb{R}^d$ with non-zero Lebesgue measure. For the discrete case with discrete-valued observations the theory is only in the beginning stage. The main theoretical problem here is modelling of large depth stochastic dependence in discrete time series $\{x_t\}$.

A universal model for describing high-order stochastic dependencies is the homogeneous Markov chain (MC(s)) of sufficiently large order $s \in \mathbb{N}$ proposed by J. Doob and E. Dynkin, defined on some probability space $(\Omega, \mathcal{F}, \mathbf{P})$ and specified by a generating equation for the conditional probability distribution

$$\mathbf{P}\{x_t = j_t \mid \mathcal{F}_{t-1}\} = \mathbf{P}\{x_t = j_t \mid X_{t-s}^{t-1} = J_{t-s}^{t-1}\} = p_{J_{t-s}^{t-1}, j_t}, \ t \in \mathbb{Z},$$

where $\mathcal{F}_{t-1} = \sigma(\{x_\tau : \tau \leq t-1\})$ is the σ-algebra; $X_{t-s}^{t-1} = (x_{t-s}, \ldots, x_{t-1})' \in \mathrm{A}^s$; $J_{t-s}^{t-1} = (j_{t-s}, \ldots, j_{t-1})' \in \mathrm{A}^s$.

This model is defined by a matrix parameter – $(s+1)$-dimensional transition probability matrix $P = p_{J_1^{s+1}}$, $J_1^{s+1} \in \mathrm{A}^{s+1}$. The number of independent parameters for MC(s) ($D_{\mathrm{MC}(s)} = N^s(N-1) = \mathcal{O}(N^{s+1})$) increases exponentially with the order s. To overcome the «curse of dimensionality» we propose to use parsimonious models (PMC(s)) for which the matrix P has the following parametric form:

$$p_{J_1^{s+1}} =:: p_\alpha(J_1^{s+1}), \ \alpha = (\alpha_1, \ldots, \alpha_m)' \in \mathbb{R}^m,$$

where α is a low-dimensional ($m = D_{\mathrm{PMC}(s)} \ll D_{\mathrm{MC}(s)}$) parameter.

We propose four main approaches for constructing high-order parsimonious Markov chains: 1) the compression of the set of possible values for the elements of matrix P; 2) the use of parametric families of discrete probability distributions; 3) the use of artificial neural networks (ANN) to approximate the dependence on past history; 4) an approach based on sufficient statistics and information geometry. Based on these approaches, we have managed to construct the following new parsimonious probabilistic models for discrete time series [10–12]:

• an s-order Markov chain with r partial connections $\mathrm{MC}(s, r)$;
• a Markov chain of conditional order $\mathrm{MCCO}(s, L)$;
• a binary conditionally non-linear autoregressive model $\mathrm{BCNAR}(s)$;
• a binomial conditionally non-linear autoregressive model $\mathrm{BiCNAR}(s)$;
• a semi-binomial conditionally non-linear autoregressive model $\mathrm{SBiCNAR}(s)$;
• a Poisson conditionally non-linear autoregressive model $\mathrm{PCNAR}(s)$;
• a neural network based model;
• a family of parsimonious models based on exponential families of probability distributions and sufficient statistics.

We have developed the frequencies based estimation method for statistical estimation of parameters for the constructed parsimonious models based on conditional multidimensional frequencies. This method allows for the construction of consistent statistical estimators and predictive statistics in an explicit form.

The directions in future development of statistical data analysis for discrete valued time series include:
• development of models, methods and software for multivariate discrete valued time series;
• formation of models, methods and software for multivariate discrete valued random fields;
• creation of mathematical theory and software for high-order Markov chains with time-varying transition matrices;
• development of stochastic volatility models.

Current trends in joint application of statistical data analysis methods and ANN. A necessary factor for the digitalisation of the economy is the processing of massive arrays of heterogeneous information with exponentially growing volumes. Currently, the universal approach considered as a «panacea» for big data is the approach based on the use of machine learning and ANN. This approach involves training an ANN (structure is selected empirically) on a training sample of a sufficiently large size. However, it is important to note three drawbacks of this empirical approach: 1) the lack of theoretical accuracy estimates for statistical inferences; 2) the absence of theoretical estimates for the required size of the training sample; 3) the lack of opportunity for the successful solution of problems in the statistical analysis of complex-structured data.

In our view, to overcome these shortcomings it is necessary to account for the fact that when constructing a solution d (an estimate, forecast or inference) from the available data X, the available prior information I must also be used: $d = f(X, I)$. The following situations are possible in this regard. If the probabilistic model, generating the data, is known, it is advisable to use classical methods from statistical decision theory. If the model is specified up to a parameter $\theta \in \Theta$, i. e. $I = M_0$, then methods of parametric statistics are applied. If the model uncertainty is even higher and it is defined by a functional set of probability distributions, methods of semi-parametric or non-parametric statistics can be employed. If prior information I is absent, one must be forced to use the ANN. It is worth note that even «minor» prior information can be useful in selecting the architecture and hyperparameters of the ANN. For example, to solve the problem in detection of statistical periodicity in a time series it is recommended to apply convolutional neural networks (CNN) with window sizes determined by the possible values of the period.

Current trends in data science

There are two main types of data depending on the way of their organisation: 1) structured data; 2) unstructured data. Structured data is information organised in a predefined, fixed format, typically in tables with rows and columns, making it easily searchable, processable and analysable by machines and humans. Unstructured data is information that lacks a predefined model or organisation, existing in native formats like text documents, images, audio, video and social media, making it hard for traditional systems to process but rich with valuable context, requiring AI and machine learning for analysis.

We will consider the second type of data. Unstructured data science involves extracting valuable insights from data that lacks a predefined format, like text, images, audio and video, using AI or machine learning techniques (natural language processing, computer vision) to find patterns, understand sentiment and fuel advanced analytics, making sense of the vast majority of enterprise data that does not fit traditional databases. Let us analyse the trends in unstructured data science.

Spiking neural networks as a third generation of neural networks. CNN currently dominate in image processing architectures. While lightweight CNN demonstrate moderate performance, they exhibit limited capacity to capture complex patterns and contextual dependencies essential for advanced tasks, thereby restricting their efficacy in practical CV scenarios. Conversely, while transformers effectively model complex relationships, their substantial computational overhead impedes compliance with computer constraints.

To overcome these limitations spiking neural networks (SNN) inspired by biological neuronal mechanisms represent a promising approach for image processing. SNN leverage event-driven dynamics and spatiotemporal encoding capabilities, combining biological plausibility with computational efficiency advantages suited to ultra-low-power environments. Although CNN have advanced image processing, SNN demonstrate superior potential in power-constrained scenarios. As a new generation of neural networks, SNN demonstrate the advantages of ultra-low power consumption and efficient computing through event-driven sparse calculations and biologically plausible spike transmission mechanisms, making them particularly suitable for image processing scenarios.

Brain-like computing can achieve architectural transitions through neuromorphic hardware. Brain-like intelligent computing has the computing advantages of low power consumption and high energy efficiency by imitating the computing architecture and methods of the human brain, providing a potential path to achieve the above technological breakthroughs. Compared with the second-generation ANN, the third-generation brain-like SNN has great potential advantages in high energy efficiency, high precision and high interpretability of remote sensing image intelligent processing due to its high bionics. Its structure is shown in fig. 3.

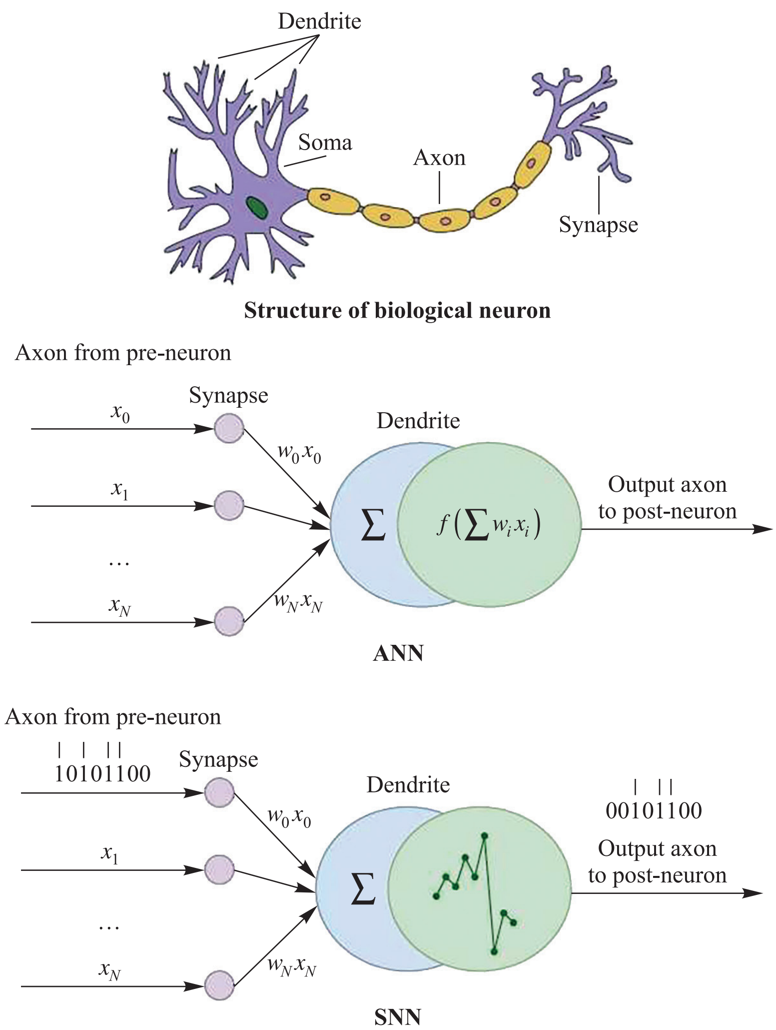

Fig. 3. ANN and SNN structure diagram

In 2019 SNN Spiking-YOLO for object detection tasks has been proposed [13]. Based on the YOLO network framework, it is improved by pulsing, which can extract multi-scale features. At the same time targeted structural changes are made to be applicable to input and output of different numbers of channels or dimensions. In 2024 X. Luo and his colleagues proposed the SpikeYOLO architecture, which combines the macrodesign of YOLOv8 and the microdesign of Meta-SpikeFormer [14]. It significantly narrows the performance gap between

SNN and ANN. Under similar parameters the performance of SpikeYOLO and YOLOv5 is comparable, and the energy efficiency is improved by 3.3 times.

SpikeYOLO is a breakthrough fusion model of SNN and a single-stage object detection framework. Its core goal is to introduce the event-driven mechanism of biological neurons into object recognition tasks. This architecture inherits the macroscopic detection paradigm of the YOLO series (such as feature pyramid and grid prediction mechanism) but replaces the convolution operation of the traditional ANN with a spiking neuron computing unit to achieve event-driven sparse computing. SpikeYOLO combines the macrodesign of YOLO with the microdesign of SNN modules.

The future trend of neural network development will be extending SNN for solving concrete CV tasks. For example, for object detection in remote sensing images.

Multi-modal data analysis. Multi-modal models refer to machine learning models capable of processing and integrating information from multiple modalities or types of data. These modalities can include text, images, audio, video and other forms of sensory input. Unlike traditional large language models that are typically designed to handle a single type of data, multi-modal models combine and analyse different forms of data inputs to achieve more comprehensive understanding and generate more robust outputs. As an example, a multi-modal model can receive a photo of a landscape as an input and generate a written summary of that place's characteristics. Also, it could receive a written summary of a landscape and generate an image based on that description. This ability to work across multiple modalities gives these models powerful capabilities.

In November 2022 OpenAI launched ChatGPT, which quickly put generative AI on the map. ChatGPT was unimodal AI designed to receive text inputs and generate text outputs by using natural language processing. GPT-4o introduced multi-modal capabilities to ChatGPT.

Key components of large multi-modal models are:

- data integration (LMMs use sophisticated algorithms to combine data from multiple sources, ensuring that the information from each modality is accurately represented and integrated);
- feature extraction (the model extracts relevant features from each type of input; for example, it might identify objects and their relationships in an image while understanding the context and meaning of accompanying text);
- joint representation (by creating a joint representation of the multi-modal data, the model can make inferences and generate outputs that consider all available information);
- cross-modal attention (techniques like cross-modal attention help the model to focus on relevant parts of the data from different modalities, improving its ability to generate coherent and contextually appropriate responses).

Currently, transformer-based multi-modal image recognition methods have shown remarkable performance in cross-modal information fusion, particularly by leveraging self-attention mechanisms to enhance interactions across modalities. Traditional multi-modal image recognition methods can be broadly categorised into three types: 1) early fusion; 2) late fusion; 3) hybrid fusion. Early fusion methods concatenate feature vectors from different modalities before classification [15]. While this approach improves the models accuracy to some extent, it ignores inherent differences in sampling rates and spatiotemporal resolutions across modalities, leading to temporal misalignment and feature heterogeneity issues [16]. Late fusion methods train separate unimodal classifiers and aggregate predictions via voting or stacking. Although this approach captures modality-specific features well, it fails to effectively capture the complementary relationships and contextual interactions between modalities, thus missing cross-modal synergistic discriminative information [17]. Hybrid fusion attempts to balance both strategies through multi-stage aggregation but still relies on static weights, unable to adapt to dynamic modality reliability, resulting in sharp performance drops in noisy environments or occluded scenarios [18].

Despite the significant progress in multi-modal image recognition, three key challenges persist: 1) reducing information loss while handling dynamic modality reliability; 2) preserving fine-grained emotional cues through multi-scale representations; 3) preventing representation drift during cross-modal semantic alignment. Traditional multi-modal image recognition methods often rely on cascaded CNN or recurrent neural networks to extract features from facial expressions, vocal cues and other modalities. However, these methods exhibit notable limitations in addressing dynamic modality reliability, multi-scale representation learning and cross-modal semantic alignment.

Multi-modal image recognition has gained significant attention due to advances in deep learning and availability of large multi-modal datasets. Despite these advancements, designing effective strategies for fusing and processing data from diverse modalities remains challenging.

Multi-modal learning is another new frontier. Traditional CV models rely on labeled data but labeling is costly and time-consuming. The move toward self-supervised learning allows models to learn from unlabeled data, using context to infer meaning. In future self-supervised learning will dominate, enabling faster model training, reduced dependency on human annotation and better generalisation across visual tasks.

CV and AI. AI is a multi-modal system that has the ability to process and understand inputs from different modes or modalities. While not dismissing the importance of advancements in language models and acknowledging the significant progress in natural language processing, as exemplified by models like GPT, it is crucial to highlight the importance of CV for AI in understanding the physical world.

Computer perception is the ability of a machine to interpret and understand visual data from the world. CV in artificial general intelligence involves the development of algorithms and models that can process and interpret visual data, such as images and videos, to extract meaningful information. These algorithms can be trained to recognise objects, people and scenes, and to understand their spatial relationships and context. With this ability AI systems can analyse and interpret visual information to make informed decisions and take appropriate actions.

Also, CV is a crucial component in AI development. Computer perception is essential for an artificial general intelligence system to interact with the environment, understand the context of its surroundings and make intelligent decisions based on that understanding.

Despite the significant progress made in computer vision, developing an AI system with human-like perception abilities remains a challenge. One of the main challenges is the ability to integrate different sensory inputs seamlessly. For example, integrating visual and auditory information to understand a scene requires complex algorithms and machine learning models that can handle the high-dimensional data from various sensory modalities.

Deep learning has been instrumental in advancing the field of perception in AI development. Deep learning models, such as CNN and recurrent neural networks, have been used to extract features from sensory inputs and learn representations of the environment. For example, CNN have been used for object recognition tasks, while recurrent neural networks have been used for speech recognition tasks.

Computer perception plays a critical role in various AI applications, such as robotics, autonomous vehicles and healthcare. For example, an AI system with perception abilities can enable robots to navigate and interact with the environment autonomously, without human intervention. In healthcare an AI system with perception abilities can enable the early detection of diseases and assist doctors in making accurate diagnoses.

However, there are also challenges associated with perception in intelligent machines. One of the main challenges is that machines perceive the world differently than humans do. For example, machines may not be able to perceive emotions in the same way that humans do. This can make it difficult for machines to interact with humans in a natural way. Additionally, machines may not be able to perceive certain types of information, such as abstract concepts or social cues.

To overcome these challenges researchers are developing new approaches to perception in intelligent machines. One approach is to use machine learning to train machines to recognise and interpret different types of input. For example, machine learning algorithms can be used to teach machines to recognise different objects in an image. Another approach is to use multiple sensors to provide machines with a more complete view of their environment. For example, self-driving cars use a combination of cameras, lidar and radar to perceive their environment.

The future of perception in AI presents both opportunities and challenges. While machines with advanced perception capabilities will be able to perform tasks that were previously impossible, there are also challenges associated with building machines that perceive the world in the same way that humans do. However, researchers are making progress in the developing new approaches to perception in machines, and it is likely that we will continue to see advances in this field in the coming years.

Short description of the contributed papers

The introductory paper of Yu. S. Kharin and S. V. Ablameyko presents current trends in statistical data analysis and information technologies. In the article of M. P. Savelov asymptotic non-negative correlatedness of some statistics used in testing the quality of random number generators is analysed. The work of A. A. Serov is devoted to reliability of two-level testing approach of the NIST SP800-22 test suite. An integer random walk $\{S_i, i \geq 0\}$ with zero drift and finite variance σ^2 is considered, and the limit theorem on convergence to the local time of a Brownian excursion is presented in the publication of V. I. Afanasyev. The article of S. E. Vorobeychikov and Yu. B. Burkatovskaya is devoted to the problem of parameter estimation of the second order Markov modulated Poisson process and a new two-staged algorithm development. The work of V. A. Voloshko considers application of the local information geometry for statistical analysis of high order binary Markov chains. In the paper of A. Yu. Kharin a problem of sequential statistical hypotheses testing for discrete random data with block structure is considered. Y. L. Orlovich and M. A. Shutro present results on a topical problem on recognition of special classes of graphs. In the article of Y. R. Adamovskiy and R. P. Bohush smoke and camera tampering detection system based on single-board computer for real-time fire monitoring is presented. The work of K. V. Andrenko, A. A. Kroshchanka, V. A. Golovko and Yu. B. Krapivin is devoted to managerial decision analysis using small language models. Real-time gait recognition system based on lightweight dual-modal pose estimation is presented in the paper of Din Aodi, Ye Shiping, A. M. Nedzved and V. S. Anosov. The paper of V. V. Krasnoproshin and A. A. Starovoitov presents a multi-model approach with vector search in operational management of critical IT service. Detection of image objects for autonomous localisation of unmanned aerial vehicles and map formation of the surrounding space is considered by V. Yu. Tsviatkou, V. V. Rabtsevich, Ma Jun and M. I. Zorko.

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