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Research on Visualization method of Data Asset Value Assessment based on artificial Intelligence

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SUMMARY: *This paper proposed a visualization method for data asset value assessment based on artificial intelligence, which supported structured measurement, dynamic scoring and intuitive interpretation of data resources. Our approach fuses graph representation learning, temporal aggregation, and visual analytics engines to estimate quality level, circulation capacity, task contribution, and risk cost from metadata, usage logs, and association records. A data set covering three business domains of retail, manufacturing and financial services and containing 4860 data assets was used for evaluation. The experimental results show that the proposed method reduces the mean absolute estimation error from 0.214 to 0.087, improves the ranking consistency from 0.79 to 0.93, and reduces the batch evaluation time from 96 s to 28 s. In the interactive analysis, the response delay is kept below 420 ms, and the accuracy of abnormal asset recognition reaches 94.1%. The visualization module further supports hierarchical exploration, confidence comparison, and value formation path tracing, showing users the ability to reliably compute, clearly explain, and deploy in real-world asset valuation scenarios.*

KEYWORDS: *Data assets; Value assessment; Artificial intelligence; Visual analysis*

1 Introduction

With the acceleration of data elements into circulation, sharing and development, data assets have shifted from ancillary information resources to computable, configurable and tradable digital objects. In the process of business collaboration, platform operation, model training and intelligent decision-making, enterprises deposit structured data, log data and label data. The usage frequency, correlation strength, update speed and application contribution of these data change, making the asset value dynamic, heterogeneous and scene-dependent. It is difficult to describe the real state of data assets in the generation, circulation, reuse and risk constraints only by relying on static ledger, experience scoring or single-dimensional statistics. The value identification process is also easily affected by dimensional fragmentation, insufficient explanation and rough display. In such a technical environment, introducing artificial intelligence modeling and visual analysis methods into data asset value assessment

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has become a new means to improve the accuracy of assessment and the transparency of results.

As an intelligent evaluation method for complex data environment, the AI-based data asset value evaluation visualization framework can extract features from multi-source heterogeneous data and present the value formation process in a graphical interactive way. On the one hand, the machine learning model is used to identify the nonlinear relationship between quality level, circulation potential, usage contribution and risk cost. On the other hand, the readability of the results is enhanced through visual mapping, hierarchical linkage and trajectory tracking, so that the evaluation output no longer stays at a single score. However, it is able to present structural sources, influence paths and confidence differences. Such a processing method is more in line with the requirements of computer journals for algorithm implementation, system design and experimental verification, and also provides technical support for data governance platform and asset operation system.

Recently, foreign scholars have carried out research on human-computer collaborative analysis, model interpretation and data-driven decision making. Andrienko et al. [1] studied visual analytics for human-centered machine learning and pointed out that model output needs to be combined with an interactive interpretation process to support users' understanding of computational results. Collaris and van Wijk[2] proposed a comparative evaluation method of contribution value map, which enhances the ability of result comparison and structure identification by graphically expressing the difference of model contribution. Roeder et al. [3] studied the information value of data-driven decision-making in credit risk management, indicating that texts and analysis signals can form quantifiable decision-making basis after computational processing. Nimmy et al. [4] systematically reviewed the research on explainable artificial intelligence in supply chain risk management, emphasizing that the explanation structure has a direct impact on the judgment credibility under high risk. De Bruijn et al. [5] proposed the explanation strategy of algorithm decision, and pointed out that there was a close connection between explanation mode, presentation logic and user understanding, which provided an important reference for the visual presentation of value evaluation results.

The existing research has provided the algorithm basis and demonstration ideas for data value analysis. However, it is still necessary to further form a unified method that links representation learning, value calculation and interaction analysis when facing data asset scenarios. Some studies focus on prediction performance. Although the evaluation results have the ability of numerical output, they lack the intuitive expression of value sources, fluctuation reasons and correlation paths. Some studies emphasize explanation and display, but lack of modeling the coupling relationship between multi-dimensional asset characteristics, which is difficult to support dynamic evaluation in high-frequency update environment. To meet these practical requirements, data asset value assessment needs to strengthen heterogeneous feature fusion at the model end, and strengthen result interpretation, hierarchical linkage and interaction tracking at the display end, so as to form a technical path that takes into account both calculation accuracy and understandability.

This paper aims to deepen the application expression of artificial intelligence methods in data asset value assessment and visual analysis, and promote data assets from static description to dynamic calculation and visual cognition. The research content of this paper focuses on three aspects: constructing an intelligent evaluation framework combining graph representation, temporal response and multi-dimensional feature aggregation, which is used to describe the dynamic generation process of data asset value. A visual coding and interactive analysis mechanism for evaluation output is established, so that the value distribution, contribution difference and anomaly source can be continuously presented. Combined with actual business scenarios, the system implementation and experimental verification are completed to verify the applicability of the method in evaluation accuracy, response efficiency and interpretation ability. The above work not only meets the requirements of algorithms, systems and verification links in the computer field, but also provides a practical method support for data asset operation, governance analysis and value discovery.

2 Theoretical basis and technical research

2.1 Data Asset representation and value assessment basis

The key to building the basis of data asset representation and value evaluation is to transform the heterogeneous information scattered in business systems, data platforms and call links into computable objects. Different from traditional ledger records, the status of data assets in the computing environment is affected by multiple factors such as metadata integrity, kinship clarity, access frequency, reuse scope, update timeliness, quality fluctuation and compliance constraints. Therefore, its value should not be directly described by a single scale indicator. The unified description should be completed through the joint modeling of structural representation, behavioral representation and benefit representation.

At the representation level, field semantics, inter-table dependencies, interface calls, log traces and permission boundaries together constitute the basic corpus of value recognition. At the evaluation level, usability, credibility, liquidity, contribution and risk cost need to be mapped to a unified dimension to form an evaluation space that supports subsequent model learning. The basic framework thus formed not only retains the technical attributes of data objects, but also retains the traces of business usage, which is convenient for subsequent algorithms to identify value differences and evolution trends.

La Rosa et al. [6] studied the visual analysis path in interpretable deep learning and pointed out that a traceable connection should be established between the internal calculation of the model and the external visual observation, which provides a basis for the structural expression of the formation process of data asset value. Brasse et al. [7] reviewed interpretable artificial intelligence in information systems, and proposed that the explanation mechanism should be embedded in the system operation link rather than remaining in the result notes, which makes the basis of value evaluation no longer limited to the score output, but to the process readable. Maack et al. [8] studied the visual analysis framework for uncertainty, emphasizing that confidence interval, fluctuation range and abnormal disturbance should be expressed synchronously, which has direct reference significance for characterizing the instability in data asset value assessment.

Saeed and Omlin[9] systematically sorted out the challenges and opportunities of explainable artificial intelligence, and proposed that the quality of explanation should be measured together with the task scenario, thus indicating that the basis of value evaluation should consider both algorithm accuracy and scenario adaptation. Sovrano and Vitali[10] proposed an objective measurement method of the degree of explainability, indicating that the explanation itself can also be quantitatively evaluated, which provides an operational theoretical support for the result credibility modeling in data asset value evaluation.

Further, the data asset representation is not a static archive, but a continuous mapping towards the computational graph. Table-level objects can be viewed as nodes, dependencies, shared relationships, and calling relationships can be viewed as edges, and statistical features, semantic embeddings, and temporal behavior can together constitute node properties. Based on this graphical representation, asset value is no longer just a linear projection of the size of the stock, but a comprehensive reflection of data quality, business contribution, circulation breadth and governance cost in the network structure.

The value assessment foundation thus established can provide stable input for subsequent artificial intelligence models, and can also provide clear coding units for visualization. Therefore, the theoretical basis of data asset value assessment should cover the four dimensions of semantic structure, behavior trajectory, benefit feedback and explanation credibility at the same time to support the subsequent method design. This point determines the long-term stability of the input boundary of the model with respect to the output quality.

2.2 Artificial Intelligence modeling and visual analysis technology

The combination of artificial intelligence modeling and visual analytics techniques provides a complete computational path from representation learning to result interpretation for data asset value assessment. In the face of data asset sets with heterogeneous sources, different granularities, and frequent updates, traditional rule matching is difficult to stably express the potential connections between assets. Methods such as graph neural network, temporal attention, contrastive learning, and multi-modal embedding can compress semantic differences in high-dimensional space, and identify the value clues of asset objects in the process of sharing, calling, migration, and reuse.

The model side is responsible for extracting joint features from metadata, quality indicators, access logs and business feedback, and output hierarchical scores, association strength and abnormal signals. Through node coloring, path expansion, confidence band display, timing linkage and view switching, the visual analysis end converts the complex calculation results into an observable, screenable and traceable interactive interface. After the linkage of the two, the value assessment is no longer a black box score, but a continuous analysis process that can be calculated, interpreted and reviewed.

Cabitza et al. [11] studied the type division of explanation concepts in interpretable artificial intelligence, and proposed that different explanation forms correspond to different usage situations, which provided a method boundary for the design of explanation layer of data asset evaluation interface. Pumplun et al. [12] proposed a design science path for interpretable machine learning decision systems, emphasizing that model deployment, user understanding, and business feedback need to be modeled in a unified way, which helps the value evaluation system move from algorithmic prototype to platform implementation. Marjanovic et al. [13] studied the knowledge transfer mechanism of visual analysis in multidisciplinary teams, and pointed out that complex analysis results can only be absorbed by non-technical roles after visual translation, which indicates that data asset value results need to be readable across roles.

Bauer et al. [14] studied the influence of explanatory artificial intelligence on user information processing, and proposed that the explanation strength would directly change the way users accept model output, which provided a basis for the hierarchical interpretation of value assessment interface. Chatzimparmpas et al. [15] systematically summarized the development status of trusted visualization in machine learning, and pointed out that the formation of trust relies on the collaborative design of display transparency, interactive feedback and uncertainty expression, which makes the combination of artificial intelligence modeling and visual analysis technology in data asset scenarios have a clearer implementation direction.

In the concrete implementation, the modeling process usually includes several steps: asset object encoding, relationship graph construction, time window segmentation, feature aggregation, score regression and result calibration. In the encoding stage, the structure attributes, quality attributes and usage attributes were mapped into a unified vector. The relationship graph stage preserves the blood, sharing and trading connections between assets.

The time window phase depicts the value fluctuation and active cycle. In the result calibration stage, confidence and error feedback are combined to correct the score offset.

Visual analytics is not only used to display final values, but also to perform model diagnosis and interactive verification. Analysts can identify the reasons for the formation of high-value assets through amplification, screening linkage and path backtracking, and can also locate the source of score oscillation through abnormal cluster comparison and confidence difference browsing.

2.3 Review of related studies

Related research shows that intelligent evaluation for complex objects has shifted from simply pursuing prediction accuracy to emphasizing structure interpretation, interaction analysis and decision support at the same time. For data asset value assessment, this turn has direct reference significance. Data assets are not isolated records, but dynamic nodes embedded in business processes, interface calls, authority control and governance policies. Therefore, the evaluation method should not only identify the attribute differences of the object itself, but also reveal its value evolution trajectory in time, relationships and scenarios.

Andrienko et al. [16] studied the method of constructing a temporal behavior recognition model based on human-in-the-loop visual analysis, and proposed that interactive feedback can continuously revise the model understanding boundary, which indicates that data asset value assessment should not stop at offline scoring, but should retain manual verification and dynamic correction entry. Basole and Major[17] studied the application opportunities of generative artificial intelligence in visualization, and proposed that automatically generating views, explanatory summaries, and analysis hints can improve the readability of complex data, which provides a new expression for multi-level presentation of value assessment results. Basole et al. [18] studied the application of visual analytics driven by artificial intelligence in complex business ecological intelligence, and pointed out that the multi-agent relationship network can reveal the hidden structure through visual linkage, which is highly consistent with the value transmission characteristics of data assets among departments, systems and processes.

Coussement et al. [19] studied the role of explanatory AI in enhancing decision making, and proposed that credible explanations can directly change the user's acceptance of the output, which suggests that value assessment systems need to include explanatory ability as a core component rather than an ancillary explanation. Rabiee et al. [20] proposed an interpretable artificial intelligence method for feature selection with enhanced supervision by integrating experts, indicating that domain knowledge embedding can improve the quality of feature selection, which provides an operational path for rule injection and feature constraint in data asset value evaluation.

Based on the above research, it can be seen that the current technology evolution has formed a clear route: the model is responsible for extracting high-dimensional features, the explanation mechanism is responsible for reducing the understanding threshold, the visual analysis is responsible for connecting the algorithm and the decision, and the expert knowledge is responsible for constrainting the scoring boundary. In order to more intuitively illustrate the cohesive relationship between these studies and the concerns of this paper, the relevant contents are summarized in Table 1.

Table 1: Correspondence between related studies and visualizations of data asset value assessment

Reference	Research Content	Technical Perspective	Implications for This Study
[16] Andrienko et al.	Human-in-the-loop visual analytics for recognizing behavioral patterns in time series	Interactive feedback for model correction	Supports manual calibration and dynamic correction in value assessment
[17] Basole and Major	Generative AI-assisted visualization generation	Automatic view generation and explanatory summaries	Supports multi-level result presentation and generation of analytical prompts
[18] Basole et al.	AI-powered visual analytics for complex business ecosystems	Multi-entity relationship network linkage	Supports asset relationship propagation and value path revelation
[19] Coussement et al.	Explainable AI for enhanced decision-making	Trustworthy explanations influence adoption	Supports the design of the explanation layer in the assessment system
[20] Rabiee et al.	Explainable AI through expert-augmented supervised feature selection	Domain knowledge-embedded modeling	Supports feature constraints and rule injection mechanisms

The combination of explainable modeling and visual interaction is no longer limited to medical, business analysis or behavior recognition scenarios, but gradually forms a transferable combination of methods. After mapping it to the data asset scenario, a more targeted technology path can be formed. The relationship graph and time series trajectory are introduced in the representation layer to identify the value accumulation of assets in the process of generation, sharing, calling and precipitation. Supervised learning and rule constraints were introduced in the evaluation layer to suppress the traction of single statistical feature on the scoring results. Belief comparison, path unrolling and anomaly localization are introduced at the presentation layer, so that the value differences from different sources can be directly observed.

This paper focuses on the integrated expression of value calculation, result interpretation and interaction analysis, which makes the data asset evaluation change from static score output to readable, searchable and traceable calculation process, and provides theoretical support for subsequent method design and system implementation. At the same time, the existing researches on single side of multi-focus model interpretation or interface expression still lack of linkage discussion between unified coding of value indicators, propagation of asset relationships, collaboration of interactive views and quantification of explanation strength.

The integration around these aspects can help to form a more stable framework of visual methods for value assessment. This kind of framework can not only serve the asset inventory in the data governance platform, but also support the computational tasks such as circulation configuration, quality tracking, operation analysis and audit tracking. It also retains a stable interface and calibration space for cross-level collaborative analysis, and ensures subsequent scalability.

3 Method design and system implementation

3.1 Data asset value assessment visualization method framework

3.1.1 Intelligent evaluation model and visual coding strategy

Data asset value evaluation is not a simple superposition of several statistical indicators, but to compress metadata semantics, calling behavior, quality status, reuse scope and risk constraints into a unified computing space, and then map the output results into observable, comparable and traceable visual objects. Based on this goal, this paper divides the intelligent evaluation model into asset joint coding layer, relationship propagation layer, time series aggregation layer, value regression layer and visual mapping layer. The input receives table structures, field descriptions, kinship links, access logs, and business feedback, and the output generates value scores, abnormal states, confidence levels, and contribution paths. The model constructed in this way not only undertakes the scoring task, but also undertakes the interpretation task, so that the data asset value evaluation can shift from simple numerical output to the synchronous expression of calculation results and formation basis.

In order to map structural attributes, quality characteristics and behavior trajectories into the same representation space, the initial joint representation of assets is as follows:

$$h_i^{(0)} = \tanh\left(W_m m_i + W_q q_i + W_u u_i + b_0\right) \tag{1}$$

where m_i represents the metadata vector of the i data asset, q_i represents the quality feature vector, u_i represents the access and reuse behavior vector, W_m, W_q, W_u represents the mapping matrix of different input channels, b_0 represents the bias term, and $h_i^{(0)}$ represents the initial embedding representation of the asset. The function of this formula is to compress heterogeneous sources, different dimensions and different granularities of information into the same vector space, so that the subsequent relationship propagation and value learning can be established on the basis of unified input, and avoid a single attribute to produce too strong traction on the overall judgment.

In order to depict the non-uniform propagation strength between assets due to kinship dependency, shared invocation and service association, the relationship weight is assigned as follows:

$$\alpha_{ij} = \frac{\exp\left(a^{\top}[U h_i^{(0)} \| U h_j^{(0)} \| R e_{ij}]\right)}{\sum_{k \in N(i)} \exp\left(a^{\top}[U h_i^{(0)} \| U h_k^{(0)} \| R e_{ik}]\right)} \tag{2}$$

where e_{ij} represents the edge attribute between asset i and asset j, including dependency type, call frequency and sharing level information, R represents the edge feature mapping matrix, U represents the node represents the transformation matrix, a represents the attention weight vector, $N(i)$ represents the neighborhood set of node i, and α_{ij} represents the attention allocation weight during relationship propagation. The function of this formula is to make high dependency, high reuse and high impact relationships occupy a greater proportion in the value propagation, so as to more truly reflect the structural role of assets in the system network.

In order to describe the cumulative response and attenuation characteristics of asset value in different time Windows, the time series aggregation is expressed as follows:

$$s_i=\sum_{\tau=1}^{T}\lambda^{T-\tau}\ Gx_i^{(\tau)}\odot p^{(\tau)} \tag{3}$$

Here, $x_i^{(\tau)}$ represents the behavior state vector of asset i at the τ time, λ represents the time attenuation coefficient, G represents the time series feature transformation matrix, $p^{(\tau)}$ represents the stage position coding, $\odot$ represents the element-wise product, and s_i represents the time series aggregation result. The function of this equation is to make the model consider short-term activity and long-term stability at the same time, which not only retains the value changes brought by recent calls, updates and flows, but also avoids unreasonable amplification of the overall score caused by a single burst behavior.

In order to map contribution, liquidity, stability, governance level and risk cost into comparable value scores, the comprehensive value regression function is as follows:

$$v_i=\sigma\left(w_c c_i+w_l l_i+w_s s_i+w_g g_i-w_r r_i+b_v\right) \tag{4}$$

Among them, c_i represents the contribution component, l_i represents the circulation capacity component, s_i represents the stability component, g_i represents the governance maturity component, r_i represents the risk reduction component, w_c, w_l, w_s, w_g, w_r represents the corresponding weight, b_v represents the bias term, $\sigma(\cdot)$ represents the compression function, and vi represents the final value score of data assets. The function of this formula is to bundle the multi-dimensional indicators into the core output under a unified scale, so that the data assets of different sources, different categories and different scales can be directly compared.

In order to clearly show the overall computational link of the intelligent evaluation model and the visual coding strategy, Fig. 1 shows the complete process from multi-source input to value output, and then to visual mapping and feedback calibration. Each module in the figure is connected in the order of "joint encoder-relation propagation-temporal aggregation-comprehensive regression-visual mapping", so that the internal calculation and interface expression of the algorithm are consistent.

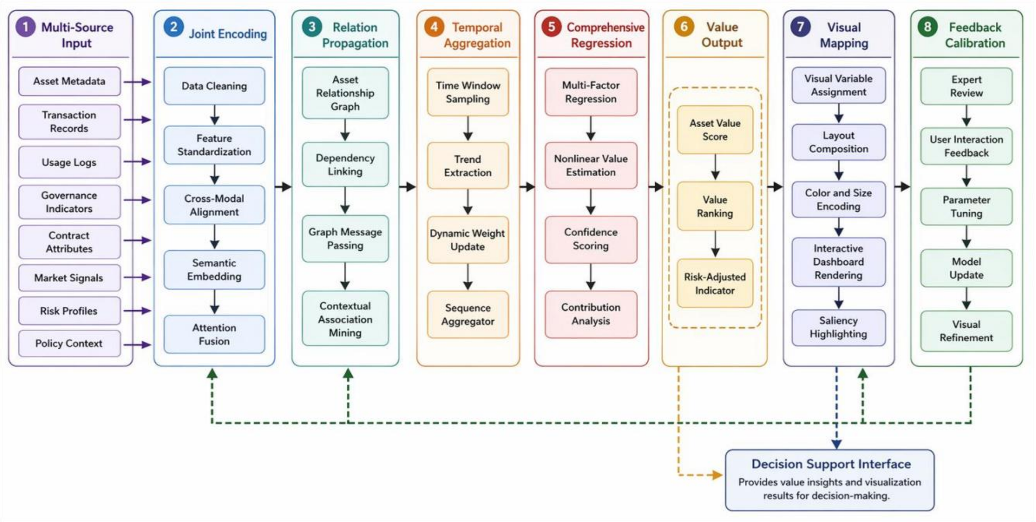

Figure 1: Flowchart of the intelligent evaluation model with the visual coding strategy

In order to ensure that the evaluation results can be directly entered into the visual analysis interface, the mapping relationship between the value results and the visual channel is as follows:

$$\Psi_i=\left(\chi(v_i),\ \eta(\rho_i),\ \omega(\delta_i),\ \kappa(z_i)\right) \tag{5}$$

Here, Ψ_i represents the visual encoding set of the i asset object, $\chi(v_i)$ represents the color mapping function, $\eta(\rho_i)$ represents the size mapping function, $\omega(\delta_i)$ represents the transparency mapping function, $\kappa(z_i)$ represents the border or texture mapping function, ρ_i represents the contribution intensity, δ_i represents the uncertainty level, and z_i represents the abnormal state. The function of this formula is to convert abstract values into visual objects stably, so that values, confidence differences and abnormal attributes can be perceived synchronously in the same interface.

Under this strategy, the model can simultaneously generate the score, confidence, anomaly label and path contribution information in one run, and then organize it into a multi-view linkage structure by the visual layer. Node color is used to visualize value gradients, size is used to express contribution scale, transparency is used to show uncertainty, and path highlighting is used to track value formation sources. After this design, the evaluation result is no longer a single score, but a complete calculation object with structural interpretation and interaction basis, which can more stably serve the subsequent data asset inventory, hierarchical management and value tracking analysis.

3.1.2 System architecture design

In order to deploy the above intelligent evaluation model into the data asset value evaluation platform stably, the system as a whole adopts a hierarchical architecture design, which is composed of data layer, calculation layer, decision layer and service layer, and is connected with the status index mechanism through a unified message bus. The goal of this architecture is not to simply stack modules, but to make collection, computation, presentation and feedback complete a closed-loop linkage under the same semantic system. The resulting system is suitable for offline batch processing, as well as online query and incremental update, and can meet the requirements of consistency, scalability and maintainability in various scenarios such as data governance, asset inventory, operational analysis and visual interaction.

In order to integrate metadata, behavior logs and business feedback before entering the model, the system input function is as follows:

$$f_t=\gamma_m E x_t^{meta}+\gamma_l L x_t^{log}+\gamma_b B x_t^{biz} \tag{6}$$

Here, x_t^{meta} represents the metadata input at time t, x_t^{log} represents the log stream input, x_t^{biz} represents the business feedback input, E, L, and B represent the feature mapping matrix of different input sources, γ_m, γ_l, γ_b represent the fusion weight, and f_t represents the unified input state. The function of this formula is to enable multi-source heterogeneous data to complete semantic alignment and scale unification before entering the computing layer, so as to ensure that the model input boundary is clear and the caliber is consistent.

In order to allocate reasonable computing resources for different tasks in high concurrency scenarios, the task priority scheduling function is as follows:

$$P_j=\mu_a a_j+\mu_u u_j+\mu_c c_j-\mu_d d_j \tag{7}$$

Here, P_j represents the priority of the j task, a_j represents the asset activity, u_j represents the user request intensity, c_j represents the computational complexity benefit term, d_j represents the expected delay cost, μ_a, μ_u, μ_c, μ_d represent the scheduling weight. The function of this formula is to make the system give priority to the task objects with high value, high activity and high interaction demand when the load fluctuates, so as to improve the overall response efficiency of the platform.

In order to reduce unnecessary computational overhead caused by repeated queries, the cache update strategy is as follows:

$$C_i^{(t+1)}=\beta C_i^{(t)}+(1-\beta)(\theta_1 h_i+\theta_2\Delta v_i+\theta_3 r_i) \tag{8}$$

where $C_i^{(t)}$ represents the cache priority state of asset i at time t, h_i represents the access popularity, Δv_i represents the range of value change, r_i represents the risk sensitivity level, β represents the history retention coefficient, and θ_1 to θ_3 represent the combination weight. The function of this formula is to make the cache system pay attention to the access frequency, value change and risk level at the same time, so that the platform gives priority to refresh the objects that are more necessary to update, and reduces the invalid recomputation.

In order to balance the response speed, synchronization error and operation stability in the service layer, the interface service objective function is as follows:

$$L_{srv}=\lambda_t T_{resp}+\lambda_e E_{sync}+\lambda_f F_{fail} \tag{9}$$

Here, T_{resp} represents the interface response delay, E_{sync} represents the front-end synchronization error, F_{fail} represents the service failure rate, λ_t, λ_e, λ_f represent the corresponding weights, L_{srv} represents the system service objective. The function of this formula is to incorporate the platform performance into the unified monitoring, so that the architecture design pays attention to the accuracy of the model and the stability of the engineering deployment at the same time.

In order to ensure that the model results, interface output, and interface rendering are consistent, the view consistency check function is as follows:

$$\Omega=\frac{1}{N}\sum_{i=1}^{N}\left(\left|\hat{v}_i^{api}-\hat{v}_i^{view}\right|+\left|\hat{\delta}_i^{api}-\hat{\delta}_i^{view}\right|\right) \tag{10}$$

Among them, $\hat{v}_i^{api}$ represents the value score returned by the interface, $\hat{v}_i^{view}$ represents the value score displayed by the interface, $\hat{\delta}_i^{api}$ represents the uncertainty index returned by the interface, $\hat{\delta}_i^{view}$ represents the uncertainty index displayed by the interface, N represents the current number of assets, Ω represents the system consistency error. The function of this formula is to ensure that the platform maintains data homology, result synonymy and interface synchronization in the process of high-frequency refresh, interactive screening and state writeback.

In order to illustrate the connection mode and data flow between each layer in the system architecture, Fig. 2 shows the overall organizational relationship from data collection, model calculation, decision convergence to service publication. Each layer in the diagram is connected by message queue, state index and interface bus, so that offline computation and online interaction can cooperate stably on the same platform.

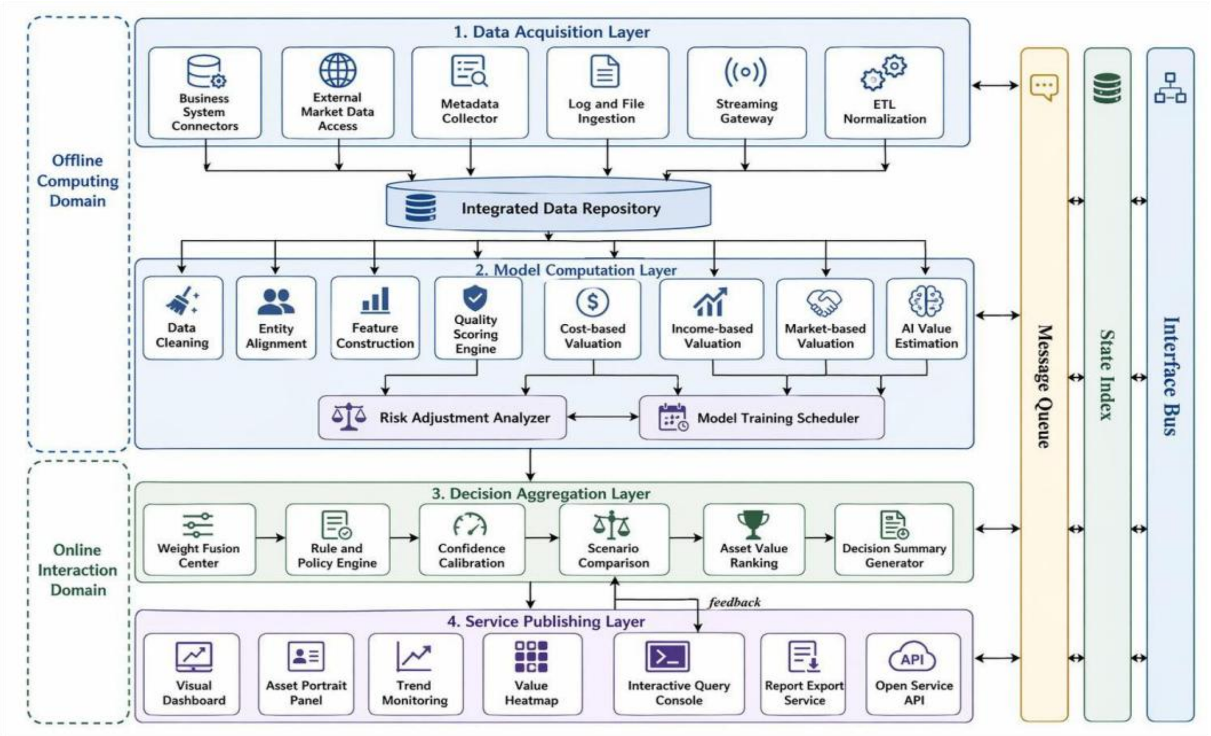

Figure 2: Data asset value assessment visualization system architecture diagram

In this architecture, the data layer is responsible for collection, cleaning, standardization and storage to ensure the consistency of input data. The computing layer is responsible for feature fusion, model inference, scheduling optimization and cache update to ensure the efficiency and stability of the evaluation process. The decision layer is responsible for aggregating value scores, path contributions and exception explanations to form readable results. The service layer is responsible for interface publishing, visual kanban board, permission control and feedback writeback, so that the system can not only provide standardized services, but also support continuous calibration. The system framework constructed in this way can not only carry the artificial intelligence evaluation model, but also stably transform the calculation results into an interactive, maintainable and extensible engineering platform.

3.2 Collaborative mechanism of value assessment and visual analysis

3.2.1 Quantitative evaluation index construction

The purpose of constructing quantitative evaluation indicators is not to mechanically add a number of statistics, but to transform the differences of data assets in the four dimensions of quality, circulation, contribution and risk into a unified evaluation space that can be learned, compared and interpreted. The value of data assets is not determined by a single frequency or a single scale. The structure quality determines the available boundary, the circulation capacity determines the diffusion range, the task contribution determines the actual benefit, and the risk cost determines the value reduction intensity. If the evaluation system only depends on the number of accesses, field scale or single income, it is easy to classify the data with high call but high noise and the data with low use but high stability into the same level, and subsequent visual analysis is difficult to show the real difference. Therefore, this paper adopts the idea of combining component modeling and unified aggregation in the quantitative index layer, so that the index system can not only retain fine-grained differences, but also support subsequent value regression and visual mapping.

In order to form a unified description of data asset quality from four aspects of completeness, consistency, timeliness and accuracy, and ensure that quality information from different sources can enter the same evaluation space, the definition of comprehensive quality indicators is as follows:

$$Q_i=\omega_1 q_i^{int}+\omega_2 q_i^{con}+\omega_3 q_i^{tim}+\omega_4 q_i^{acc} \tag{11}$$

Here, Q_i represents the comprehensive quality score of the i data asset, q_i^{int} represents the integrity component, q_i^{con} represents the consistency component, q_i^{tim} represents the timeliness component, q_i^{acc} represents the accuracy component, and ω_1 to ω_4 represent the corresponding weights. The meaning of this formula is to compress the discrete quality inspection results into a comparable and uniform quantity, so that quality is no longer just a precheck condition, but a core input in value evaluation.

In order to continuously express the circulation intensity of data assets in the process of sharing propagation, interface call and cross-domain reuse, and suppress the local distortion caused by extreme high-frequency access, the circulation capacity measurement function is defined as follows:

$$L_i=\log(1+n_i^{call})+\phi_1 n_i^{share}+\phi_2 d_i^{cross}+\phi_3 r_i^{reuse} \tag{12}$$

Here, L_i represents the asset circulation ability score, n_i^{call} represents the number of calls, n_i^{share} represents the number of sharing, d_i^{cross} represents the depth of cross-domain usage, r_i^{reuse} represents the reuse intensity, and ϕ_1 to ϕ_3 represent the regulation coefficient. The purpose of this formula is to combine frequency, diffusion, and reuse into the same metric, rather than only judging whether a data is of high value based on a single visit. After introducing logarithmic compression, extreme high-frequency objects will not stretch the sorting distance infinitely, making the circulation index closer to the true diffusion ability.

In order to clearly show the connection relationship of quantitative indicators from original features to component calculation and then to unified aggregation output, Fig. 3 shows the construction process of quantitative evaluation indicators of data assets. From left to right, the figure shows the formation process of quality component, circulation component, contribution component and risk reduction term in turn, and then the final value score is output by the aggregation layer, so that the index structure is consistent with the model link.

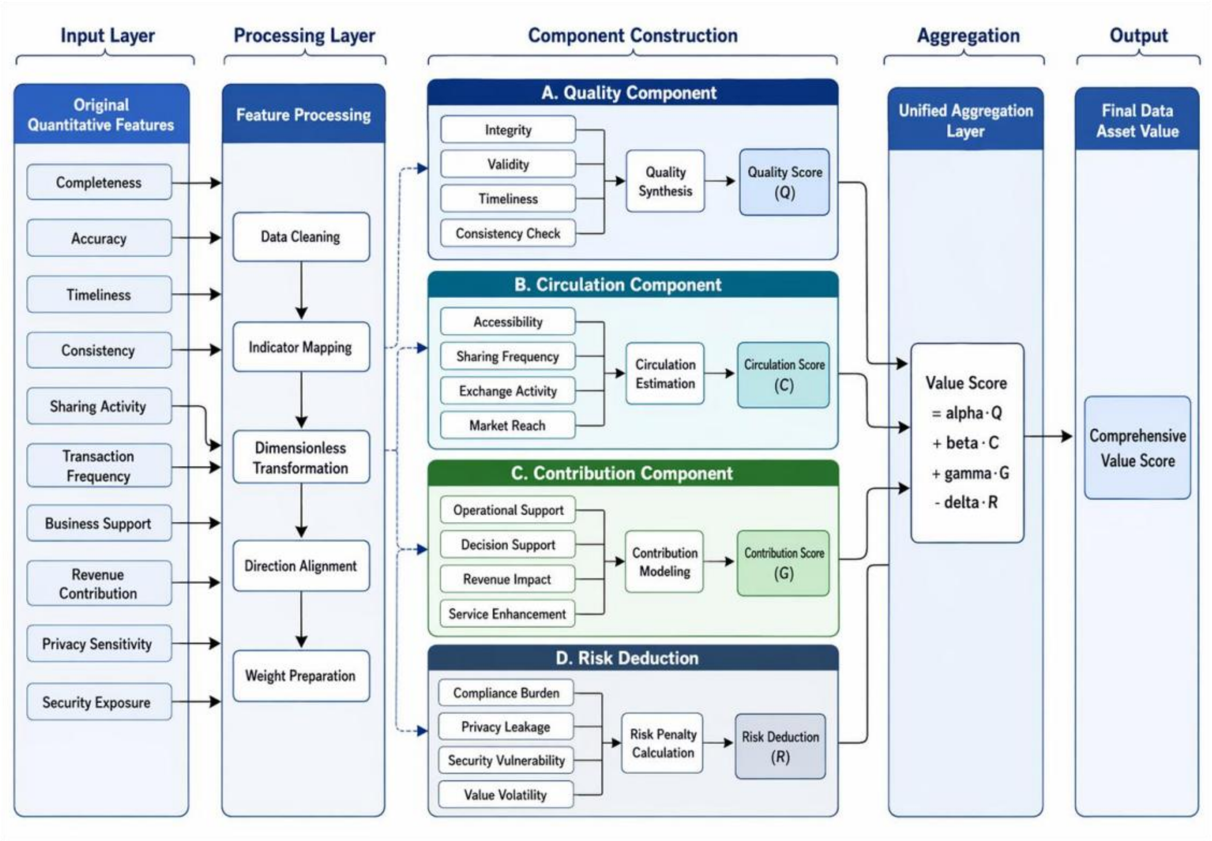

Figure 3: Flow chart of building quantitative evaluation indicators for data assets

In order to make the supporting effect of data assets on model training, business analysis and decision-making tasks form a regressible contribution, and distinguish the use intensity from the actual gain, the contribution index function is defined as follows:

$$C_i=\frac{1}{M}\sum_{m=1}^{M}\left(\alpha_m u_{im}+\beta_m g_{im}-\gamma_m e_{im}\right) \tag{13}$$

where C_i represents the contribution score of the asset, M represents the total number of tasks, u_{im} represents the intensity of use of asset i in task m, g_{im} represents the performance gain brought by the asset, e_{im} represents the error cost caused by redundancy, offset or noise, and $\alpha_m,\beta_m,\gamma_m$ represent the task weight. The function of this formula is to avoid simply equating "frequently used" with "truly creating value". At the same time, it can also identify those data objects that are not used frequently but have obvious support for the key task effect, so that the contribution evaluation is more in line with the actual performance in the computing scene.

In order to compress quality, circulation, contribution, and risk reduction into standardized value scores and provide direct outputs for ranking, clustering, and visual coding, the composite value scoring function is defined as follows:

$$V_i=\sigma\left(\theta_q Q_i+\theta_l L_i+\theta_c C_i-\theta_r R_i+b\right) \tag{14}$$

where V_i represents the final value score of data assets, Q_i represents the quality score, L_i represents the circulation score, R_i represents the risk reduction term,$\theta_q,\theta_l,\theta_c,\theta_r$ represent the combination weight, b represents the bias term, and $\sigma(\cdot)$ represents the compression function. The function of this formula is to project multiple components to the same scale, so that different categories, different sources and different scales of data assets can be directly compared, and also provide a stable basis for the subsequent hierarchical display and anomaly identification of the interface.

In this index system, the quality component plays the role of basic screening, the circulation component describes the diffusion boundary, the contribution component identifies the task value, and the risk item is responsible for suppressing the ranking shift of high uncertainty objects. The quantitative evaluation structure formed in this way can not only enter the model training, but also directly serve the color layering, size mapping and anomaly labeling of the visual analysis interface, so as to establish a stable correspondence between numerical output and visual expression.

3.2.2 Result interpretation and visual interaction rules

The goal of establishing the rules of result interpretation and visual interaction is not to add a paragraph of explanation after the scoring is completed, but to organize the value output, confidence state, path contribution, abnormal significance and user action into an explanation structure that can be continuously linked. When data asset value assessment enters the visual analysis environment, users not only pay attention to the high and low scores, but also pay attention to where the scores come from, what triggers the fluctuations, what kinds of factors cause the anomalies, and why the ordering of different assets is close or separate. If there is no unified computing foundation in the interpretation layer, the filtering, drilling and interaction in the interface will stay in static browsing and cannot support real analysis. Therefore, this paper introduces five types of rules in the explanation layer, such as confidence estimation, path attribution, abnormal saliency, interaction focus and view synergy, so as to form a closed loop between value results and visual interaction.

In order to make the credibility of the model output synchronized with the final value score, and reflect the deviation degree between the current result and the historical stable state, the confidence estimation function is defined as follows:

$$\Gamma_i = \exp\left(-\frac{|V_i - \bar{V}_i|}{\tau_1}\right) \cdot \exp\left(-\frac{\delta_i}{\tau_2}\right) \tag{15}$$

Here, Γ_i represents the result confidence of asset i, V_i represents the current predicted value score, $\bar{V}_i$ represents the central value of the historical stability interval, δ_i represents the local fluctuation amplitude, and τ_1, τ_2 represent the scale parameters. The function of this formula is to incorporate the offset degree between the current output and the historical state, as well as the fluctuation intensity of the result itself into the credibility calculation at the same time, so that the high-scoring but unstable objects will not be misjudged as high-trusted assets, and the transparency and shadow strength of the visual interface have a clear numerical source.

In order to make the value formation process be traced to the specific path and the specific adjacent relationship, and the propagation results fall on the interpretable structural unit, the path contribution attribution function is defined as follows:

$$A_{i \leftarrow j}^{(p)} = \frac{\alpha_{ij}^{(p)} \cdot \|h_j^{(p)}\|_2}{\sum_{k \in N(i)} \alpha_{ik}^{(p)} \cdot \|h_k^{(p)}\|_2} \tag{16}$$

Here, $A_{i\leftarrow j}^{(p)}$ represents the path contribution ratio of node j to node i in the p layer propagation, $\alpha_{ij}^{(p)}$ represents the attention weight of this layer, $h_j^{(p)}$ represents the representation vector of node j in this layer, $\|\cdot\|_2$ represents the two-norm, and N(i) represents the neighborhood set of node i. The function of this formula is to decompose the abstract relationship propagation results into specific path contributions, so that the interface can show "where the high value comes from" and "which link the fluctuation is conducted along", so that the explanation truly falls into the structural level rather than staying on the generalization description.

In order to map value deviation, quality anomaly and risk mutation into the same anomaly space and form a comparable warning intensity in the interface, the anomaly significance function is defined as follows:

$$Z_i=\frac{|V_i-\mu_V|}{\sigma_V}+\lambda_1\frac{|Q_i-\mu_Q|}{\sigma_Q}+\lambda_2\frac{|R_i-\mu_R|}{\sigma_R} \tag{17}$$

Here, Z_i represents the abnormal significance of asset i; μ_V,μ_Q,μ_R represent the mean value, quality and risk dimensions respectively; $\sigma_V,\sigma_Q,\sigma_R$ represent the corresponding standard deviation respectively; λ_1,λ_2 represent the adjustment weights. The function of this formula is to project the anomalies from different sources to a unified scale, so that the objects with high fluctuation, high risk and high deviation can be recognized at the same time, and also provide a unified basis for the border texture, warning color block and anomaly sorting in the interface.

In order to enable the user to automatically focus on the objects that are more worthy of analysis during the filtering, zooming in and drilling process, and reduce the occupation of attention by invalid information, the interactive focus scoring function is defined as follows:

$$F_i=\psi_1V_i+\psi_2\Gamma_i+\psi_3Z_i+\psi_4H_i \tag{18}$$

Here, F_i represents the focus score of asset i under the current interaction round, V_i represents the value score, Γ_i represents the confidence, Z_i represents the abnormal salience, H_i represents the historical attention heat, and ψ_1 to ψ_4 represent the combination weight. The function of this formula is to automatically improve the display priority of high-value, high-change and high-concern objects according to the current analysis goal, so that the interface does not evenly spread out all objects, but actively guides the analysis eye into the more discriminative area.

In order to ensure that the node view, path view, table view and information panel maintain consistent semantics in the process of linkage switching, the view coordination constraint function is defined as follows:

$$C=\frac{1}{N}\sum_{i=1}^{N}\left(\left|s_i^{node}-s_i^{table}\right|+\left|s_i^{path}-s_i^{panel}\right|\right) \tag{19}$$

where C represents the view synergy error, s_i^{node} represents the state value in the node view, s_i^{table} represents the state value in the table view, s_i^{path} represents the state value in the path view, s_i^{panel} represents the state value in the information panel, and N represents the current number of displayed objects. The function of this formula is to constrain the state deviation between multiple views, ensure that the ordering, exception and confidence information seen by users in different Windows are consistent, and avoid the fracture of interpretation results in the process of interface switching.

Under the joint action of these rules, the result interpretation is no longer an additional explanation, but a calculation step running synchronously with the value evaluation process. The belief rule determines transparency and shadow strength, the path attribution rule determines line highlight and source expansion, the abnormal saliency determines border texture and warning mark, the interactive focus rule determines the default display order, and the view coordination rule ensures that multiple Windows are always in the same state. The explanation and interaction mechanism formed in this way enables the value evaluation results to be continuously observed, tracked layer by layer and dynamically corrected, and also enables the subsequent experimental evaluation to be carried out from three levels: calculation accuracy, interpretation effect and interface consistency.

4 Experimental Evaluation

4.1 Experimental Design

In this section, the international data asset evaluation scenario is used to carry out the experimental verification. The experimental data is composed of public data lake metadata sets, cross-border e-commerce transaction logs, enterprise-level API call records and data quality audit samples, covering three business domains of retail, manufacturing and financial services. A total of 4860 data asset objects, 2.14 million call events and 38 business subsystem relationship records are formed. In order to ensure that the evaluation process conforms to the computer experiment specification, all samples are anonymized and uniformly converted into structured inputs containing pattern information, blood path, access frequency, reuse depth, quality score and risk marker. The experimental platform is deployed on a dual-channel Xeon Gold server, 128GB memory and RTX 4090 environment. The back-end uses Python, PyTorch and FastAPI, and the front-end uses Vue and ECharts to realize multi-view interaction. The data is divided into training set, validation set and test set by 70%, 20% and 10%. AdamW optimizer is used in the training phase, the initial learning rate is set to 2×10^{-4}, the batch size is 64, the maximum number of rounds is 80, and the early stopping mechanism is used to control overfitting. In the evaluation stage, the mean absolute error, sorting consistency, anomaly recognition accuracy, view response time delay and batch evaluation time are selected as the core indicators. At the same time, the traditional weighted scoring model and the simplified model without relation propagation module are constructed as a control to test the comprehensive performance of the proposed method in terms of value estimation accuracy, interpretation validity and system availability. All experiments were performed five times independently under the same configuration, and the mean and variance of each index were reported to verify the stability and repeatability of the results.

4.2 Effect Evaluation

In order to verify the comprehensive performance of the proposed method in data asset value evaluation and visual analysis scenarios, this paper compares the artificial intelligence visual evaluation model with the traditional weighted scoring model and the simplified model with the relationship propagation mechanism removed.

In order to compare the overall differences of different models in core indicators, Table 2 summarizes the results of the three types of methods in terms of error control, ranking effect, anomaly recognition and system response.

Table 2: Comparison of comprehensive performance of different methods

Method	Mean Absolute Error	Ranking Consistency	Anomaly Detection Accuracy / %	View Response Latency / ms	Batch Evaluation Time / s
Traditional Weighted Scoring Model	0.214	0.79	81.6	512	96
Simplified Model without Relation Propagation	0.146	0.86	88.4	463	43
Proposed Method	0.087	0.93	94.1	418	28

Table 2 shows that the traditional weighted scoring model is at a low level in all five indicators, especially in error control and ranking consistency. Although the simplified model without relationship propagation has an improvement over the baseline method, there is still a significant gap between its ranking consistency and anomaly recognition ability and the full model because it fails to make full use of the kinship connection, shared link and cross-domain multiplexing structure between assets. The proposed method achieves the best results on all indicators, in which the mean absolute error is reduced by 59.3% and the ranking consistency is improved by 17.7% compared with the traditional model, indicating that the joint mechanism of relationship propagation, time series aggregation and interpretation constraints has a significant support role for data asset value estimation.

In order to further observe the distribution of errors in different business domains and different value hierarchies, Fig. 4 shows the mean absolute error heatmap. In the figure, the error of the high-value asset area in the retail domain is 0.082, the error of the median asset area in the manufacturing domain is 0.089, and the error of the low-value asset area in the financial service domain is 0.094. The maximum error of the nine cells is only 0.103, and the minimum error is 0.071. The overall fluctuation is small. As a comparison, the error of the traditional model reaches 0.247 in the high-value asset area of financial service, and 0.221 in the median asset area of manufacturing domain, and the error concentration area is more obvious. This indicates that the model does not show significant drift due to high-frequency calls or complex kinship links, and the value regression results have good structural robustness.

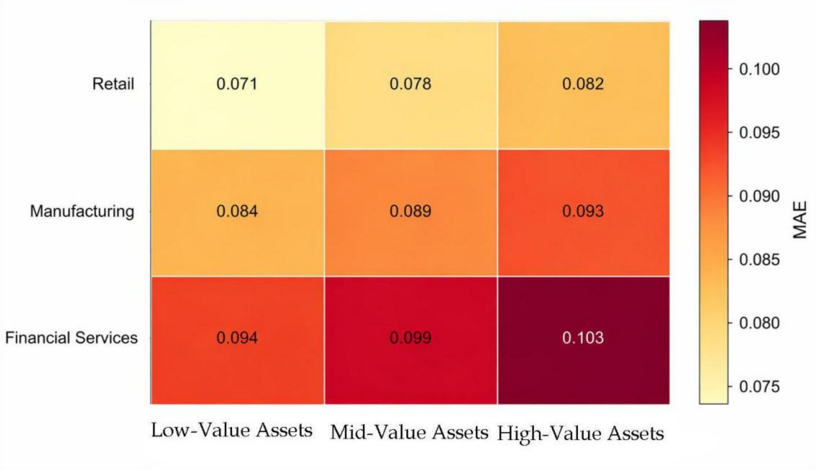

Figure 4: Error heatmaps for different business domains versus value hierarchies

In order to compare how well the ranking results hold under different value segments, Fig. 5 plots the radar plots of ranking consistency for three classes of methods over five value intervals. The consistency of the proposed method from the lowest segment to the highest segment is 0.91, 0.92, 0.93, 0.94 and 0.95, respectively. The overall contour is balanced and the level transition is smooth. The corresponding values of the simplified model are 0.82, 0.85, 0.87, 0.88 and 0.89, while those of the traditional model are concentrated between 0.76 and 0.84, especially in the area of medium and high value assets. The ordering relationship between high-value assets, edge assets and middle layer assets can be stably preserved, which makes the hierarchical display, priority screening and path backtracking in the subsequent interface more credible.

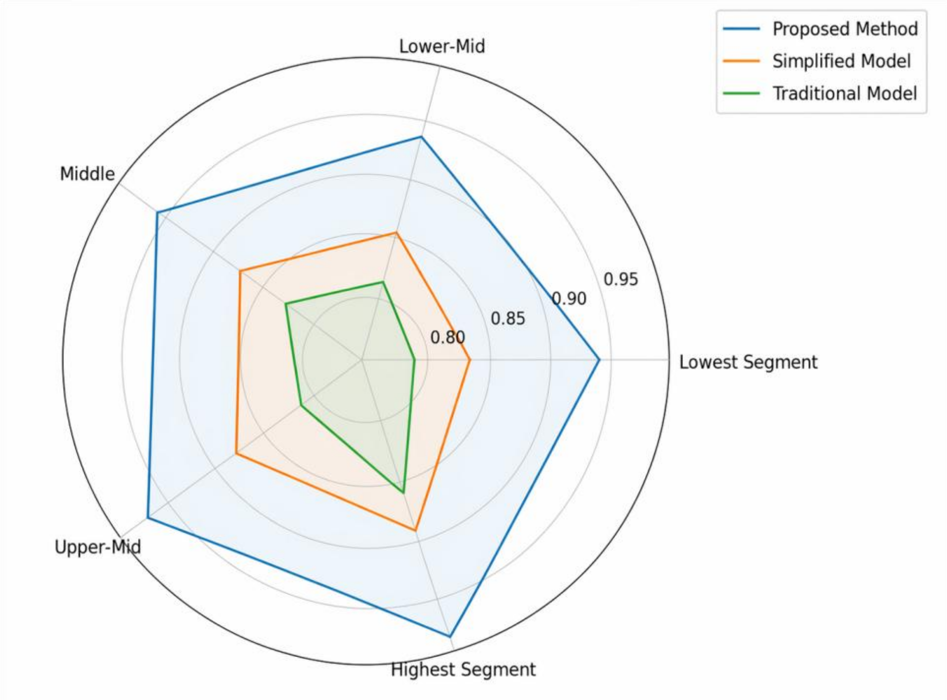

Figure 5: Radar plot of rank consistency for different value segments

To show the distribution difference between normal assets and abnormal assets in the feature space, Fig. 6 uses a scatter plot to show the recognition results of 4860 samples in the test set, including 4546 normal assets and 314 abnormal assets. The results show that the abnormal assets are mainly concentrated in the high volatility and high deviation region, and the normal assets are concentrated in the low volatility and low deviation region, and the distribution boundary of the two types of samples is clear. Among the 314 real abnormal objects, 295 were accurately identified, and only 19 of them fell near the boundary area. Out of 4546 normal objects, 4332 were correctly judged and 214 were misidentified as abnormal. A small number of misjudged samples mainly appear in the data objects with high volatility but low risk level. The results show that the proposed method can distinguish normal assets and abnormal assets more stably, and maintain high recognition accuracy.

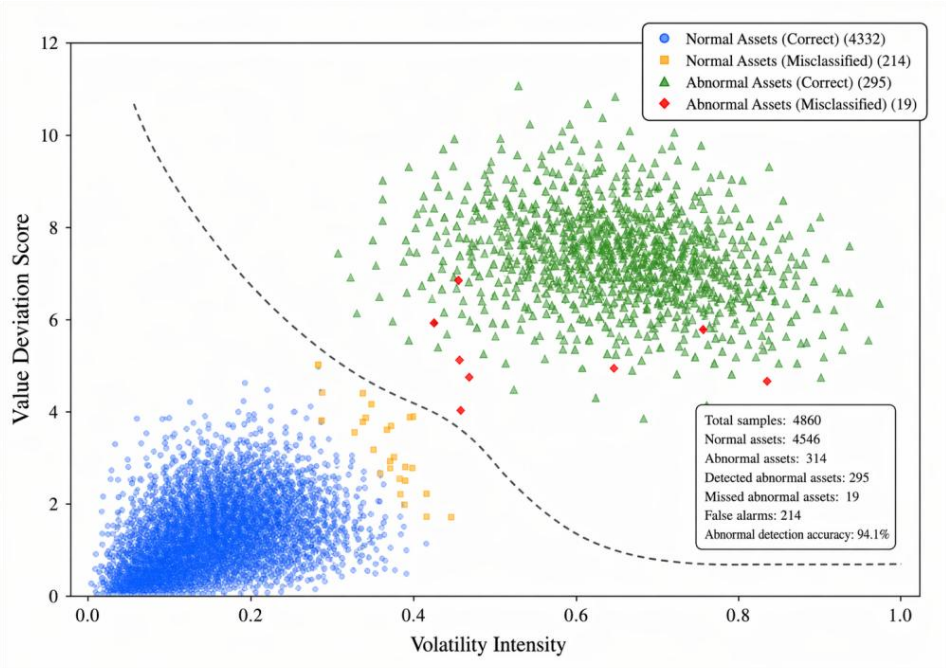

Figure 6: Scatter plot of abnormal asset identification results

To evaluate the real-time performance of the system during the actual interactive analysis, Fig. 7 presents the violin plot of the view response delay. The median response time was 362 ms for asset filtering operations, 418 ms for path unwrapping, 395 ms for hierarchical drillers, and 406 ms for anomaly focusing. The main distributions of the four types of operations are concentrated in the range of 350 ms to 450 ms, and only a few path expansion requests are closer to 500 ms. In contrast, the traditional model has a long-tail delay of more than 600 ms in both path expansion and anomaly focus operations. The filter, expand, focus, and drill operations in the interface can be maintained within a relatively stable delay range, which indicates that the backend cache update, result indexing, and view coordination mechanisms can support continuous interaction in actual analysis scenarios.

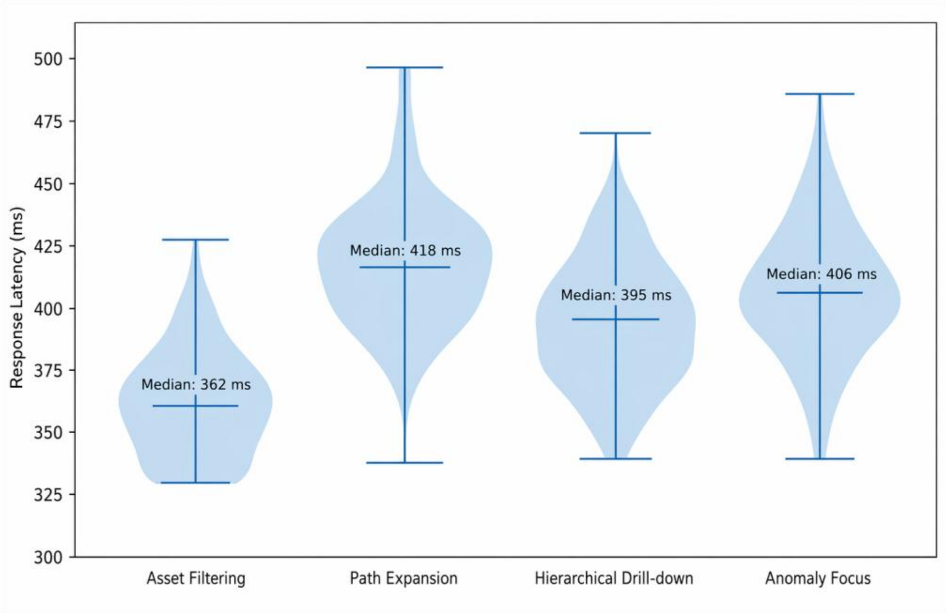

Figure 7: Violin plot of response time delay for different interaction operations

In order to analyze the influence of each component module of the model on the results, Table 3 presents the ablation experiment results. The experiment removed the relationship propagation layer, time series aggregation layer, confidence mapping layer and interactive feedback module respectively to investigate the effects of missing different modules on error control, sorting stability, anomaly recognition and response performance. This table reflects the module contribution difference and is not repeated with the distribution experiment in the above figure.

Table 3: Comparison of the results of ablation experiments

Model Setting	Mean Absolute Error	Ranking Consistency	Anomaly Detection Accuracy / %	View Response Latency / ms
Without Relation Propagation Layer	0.119	0.88	89.6	401
Without Temporal Aggregation Layer	0.127	0.87	88.9	395
Without Confidence Mapping Layer	0.101	0.91	91.8	416
Without Interactive Feedback Module	0.095	0.92	92.4	427
Full Model	0.087	0.93	94.1	418

Table 3 shows that the relationship propagation layer and time series aggregation layer have the greatest impact on error control and ranking consistency. After removal, the mean absolute error increases to 0.119 and 0.127 respectively, and ranking consistency decreases to 0.88 and 0.87 respectively. The belief mapping layer and the interactive feedback module have a more direct impact on the anomaly recognition rate and the interface operation stability, indicating that the result interpretation and view linkage are not ancillary functions, but a necessary part of the evaluation closed loop.

Synthesizing all the results, it can be seen that the proposed method is significantly better than the control methods in terms of value calculation accuracy, ranking preservation ability, anomaly recognition accuracy and visual interaction stability. The radar chart results show that the ranking structure remains stable, and the scatter distribution results show that the abnormal discrimination boundary is clear. Ablation experiments further prove that relationship propagation, time series aggregation, confidence mapping and interactive feedback modules have irreplaceable roles.

4.3 Discussion

The visualization method of data asset value assessment constructed in this paper shows strong stability in the multi-source heterogeneous data environment. Compared with the traditional weighted scoring method, this method no longer relies on fixed weights to statically rank asset objects, but describes the value formation process through relationship propagation, time series aggregation and interpretation constraints. Therefore, it achieves better results in mean absolute error (MAE), ranking consistency and anomaly recognition accuracy. In the experiment, the mean absolute error is reduced to 0.087, and the ranking consistency is improved to 0.93, indicating that the model can better maintain the continuity of value judgment across business domains and levels. The response time of the interactive level is stable around 418ms, which also indicates that the proposed method achieves a balance between explanation display and online analysis. On the other hand, this method is more suitable for data governance scenarios with clear kinship, call links and quality records. When the source of asset objects is extremely dispersed and the quality of labels is uneven, the dependence of the model on edge structure and historical trajectory will be more obvious. On the whole, the advantages of the proposed method are not only reflected in the numerical results, but also in the analysis capabilities of traceable results, undeployable paths, and locable anomalies, which make the data asset evaluation shift from static score output to structured cognitive process, and also provide a stable technical foundation for subsequent platform deployment. At the same time, compared with the model that only focuses on single scoring, the proposed method is closer to the actual system usage in terms of interface linkage, result verification and analysis loop closure. The result is consistent with the change trend of the chart data mentioned above, and can form a relatively complete mutual corroboration.

5 Conclusion

Focusing on the collaborative task of data asset value assessment and visual analysis, this paper constructs an artificial intelligence method framework that integrates relationship propagation, time series aggregation, value regression and interactive interpretation, and completes experimental verification on multiple business domain samples. The results show that the proposed method can improve the ranking consistency and anomaly identification accuracy while maintaining a low estimation error. It can also support the path unrolling, belief display and linkage analysis for asset objects. Compared with the static scoring method, the proposed method is more suitable for dealing with the collection of data assets with shared links, call records and quality traces. It should be noted that there are still some limitations in this paper. First, although the experimental samples cover multiple business domains, the source of assets is still mainly structured data, and the value expression of unstructured objects has not been fully developed. Second, some interpretation rules depend on the historical trajectory and edge structure quality, and the stability of the results will be affected when the log is missing or the blood record is incomplete. Third, the current system focuses on single platform analysis, and there is still room for expansion of the adaptability to cross-organizational asset flow scenarios. Future research can continue to introduce multi-modal representation, federated evaluation mechanism, and lightweight online update strategy to enhance the generalization ability, migration ability, and real-time deployment level of the method in complex environments. At the same time, the generative visual summary and adaptive interactive recommendation mechanism can be combined in the future to further compress the analysis path length, reduce the understanding cost of non-technical users, and improve the continuous use value of asset evaluation results in governance audit, circulation configuration, and operation monitoring.

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