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Digital Transformation Empowers Growth Marketing with Marketing Data Analysis Integration and Real-Time Display Strategy

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Abstract: In the context of digital transformation empowering growth marketing, marketing data analysis integration and real-time display strategies need to break through the limitations of traditional tools to achieve efficient decision support. The HAIChart system proposed in this study constructs a "generation feedback optimization" closed loop through a reinforcement learning framework, integrating artificial intelligence computing power with user intent insight to address the dual pain points of time-consuming interactive tool operations and lack of understanding of automatic tool intent. The system adopts a dual module design of offline learning and online recommendation, explores the visualization space using Monte Carlo graph search algorithm, and dynamically adapts to requirements by combining composite reward functions (integrating data characteristics, visualization rules, and user preferences in three dimensions); By using a visual prompt mechanism to guide user feedback, multiple rounds of iterative optimization of recommendation quality can be achieved. Experimental verification shows that in the VizML dataset Hit@1 The indicator reached 79. 3%, and the P @ 10 of KaggleBench data query task increased to 79. 2% in the third round. User satisfaction was significantly better than tools such as Voyager2. This achievement constructs a growth oriented marketing intelligent visual recommendation system, which realizes real-time integration of multi-source marketing data and dynamic visualization of core indicators, deeply integrates user intentions to enhance strategic accuracy. In the future, we will expand multimodal interaction and dynamic data support, strengthen decision interpretability and real-time performance, and promote the dual improvement of marketing efficiency and growth potential.

1. Introduction

In the data-driven era, data visualization serves as the core bridge connecting complex data with decision insights, and its value lies in improving data understanding efficiency through visual expression. With the surge in data volume and the upgrading of analysis requirements, how to efficiently generate insightful visualizations has become a common challenge for both academia and industry. The existing tools are mainly divided into two categories: interactive and automatic. Interactive tools[1] give users high flexibility, but require time-consuming attempts and rely on professional knowledge, making novice users easily blocked; Automated tools generate recommendations through rules or learning algorithms, but often suffer from recommendation bias due to a lack of user intent understanding, which limits personalization and exploration. Visualization based on natural language queries simplifies creation through intent mapping, but requires users to explicitly query; Although the application of reinforcement learning in visualization shows potential, it faces challenges such as insufficient model diversity, difficulty in integrating user preferences, and complex data processing. Aiming at the above pain points, a human-machine collaborative visualization recommendation strategy - HAIChart system [2] is proposed. Its core motivation lies in integrating artificial intelligence computing capabilities with user creative thinking, balancing efficiency and personalization through a two-stage architecture of "offline learning online recommendation": constructing a multi dataset corpus in the offline stage, pre training composite reward functions to capture visual features and quality correlations; In the online stage, the Monte Carlo graph search algorithm is used to traverse the visualization space, combined with a composite reward function to dynamically evaluate quality, and visual prompts are used to guide users through multiple rounds of feedback, forming a closed loop of "initial recommendation user adjustment iterative optimization".

2. Correlation theory

2. 1. Visual query and its query graph framework

In data-driven decision-making, data visualization[3]plays a crucial role by transforming complex data into intuitive visual forms, but traditional methods are difficult to efficiently address the dynamic exploration needs of large-scale datasets. This study proposes a four step visualization method: identifying chart types (bar/scatter plots) → mapping data to visual channels (coordinate axes/colors) → data preprocessing (grouping/sorting) → generating result V. Innovatively, DAG "visual query graph" modeling is used, with nodes as processing units, edge weights evaluating conversion efficiency, and root to leaf paths forming a logical chain. The framework achieves interpretability and traceability through clear decision paths, combined with weight optimization, to improve the efficiency and accuracy of complex scene generation, providing a systematic solution for intelligent visualization. Taking the flight delay dataset as an example, visual queries can be visualized as bar charts with "x-axis encoded cities and y-axis displaying average delays" to reveal the delay trends of different cities; The visual query graph uses a hierarchical structure (such as chart type layer, encoding layer, and conversion layer) to structurally represent all possible paths, such as the "bar chart city grouping average delay aggregation" path directly corresponding to generate a specific bar chart. This method not only provides a theoretical basis for automated generation of high-quality visualizations, but also promotes a deeper understanding of visual encoding strategies and transformation techniques in data exploration through a structured framework, ultimately supporting more accurate data analysis and decision-making.

2. 2. Problem definition and framework exploration of multi round visual recommendation

This study focuses on the core issue of efficiently filtering "high-quality" visualizations (i. e. visually relevant and insightful presentations) from relational data table D - traditional manual selection relies on user expertise and is inefficient, while existing single round machine learning recommendations are difficult to meet diverse needs (such as building dashboards that require multi visualization collaboration). To solve this problem, a multi round visual recommendation strategy is proposed: through n rounds of interaction, a set of visualizations (with visual prompts attached) are recommended to the user in each round, and the user gradually optimizes the recommendation results after selection, ultimately forming a set that accurately reflects the user's preferences. This strategy captures dynamic requirements through iterative feedback, improving the quality of results and user satisfaction; Enhance interactive intuitiveness through visual cues and promote deep exploration of data. Introducing visual query graphs (DAG modeling structured operations) opens up a new perspective for data exploration, deepens the understanding of visual encoding and transformation logic, and lays the theoretical foundation for automated high-quality visualization generation; The multi round recommendation strategy demonstrates the potential for iterative optimization, supporting precise decision-making insights and efficient data analysis.

3. Research method

3. 1. Multi round visual recommendation framework driven by reinforcement learning

This study proposes the HAIChart system, which adopts a two-stage architecture of "offline learning online recommendation" to overcome the dual bottleneck of improving data visualization efficiency and quality. Constructing a corpus that integrates multiple datasets, visualized results, and quality ratings during the offline phase, and mining the deep correlation between visualized features and quality indicators through pre trained composite reward functions; In the online stage, the Monte Carlo graph search algorithm is used to efficiently traverse the visualization space, combined with a composite reward function to dynamically evaluate the quality of the results. The system guides users through multiple rounds of interaction through visual prompts, forming a closed-loop optimization mechanism from initial recommendations to user feedback, ultimately achieving a dual improvement in visual generation efficiency and quality. The core innovation of this system lies in modeling visual recommendation as a Markov decision process[4], defining five elements: state, action, agent, reward, and environment. Optimize interactive decision-making through reinforcement learning to improve the matching between recommendation results and user needs. This framework not only significantly improves the efficiency of visualization generation and user satisfaction, but also deepens users' insights into data through iterative feedback, providing a cutting-edge technological paradigm for the field of automated data visualization.

3. 2. Research on Visual Recommendation Method Based on Monte Carlo Graph Search

For example, similar query paths in graph structures (such as Q1 and Q2 with only differences in chart types) can share node information, while tree structures cannot achieve this advantage due to strict parent-child relationships. The MCGS algorithm process consists of four stages: the selection stage uses the Upward Bound (UCB) algorithm to balance exploration and utilization, and the formula is used for

$$UCB(i) = X_i + C2 \ln n / n_i \quad (Formula\ 1)$$

For the average reward of child nodeX_i, n is the number of visits to the current node, n_in is the number of visits to child node i, and C is the balance parameter; Introducing pruning algorithms based on visualization domain knowledge during the expansion phase to screen high potential value operations; Construct effective queries during the simulation phase and score them using a composite reward function; In the backpropagation stage, the score will be traced back to the root node along the path, and the node reward value and visit frequency will be updated to optimize subsequent decisions. Experimental verification shows that this method significantly outperforms traditional methods in search efficiency and recommendation quality, supporting technological innovation in automated visualization generation.

3. 3. Knowledge pruning reward driven adaptive visual recommendation framework

This article focuses on improving the efficiency and recommendation quality of visual search, proposing a pruning algorithm based on domain knowledge and an adaptive random exploration strategy, and designing a composite reward function to comprehensively evaluate the quality of visualization. The pruning algorithm[5]uses the function L (S, A) combined with data type, chart type, and encoding rules to filter for valid operations (such as excluding sum/avg aggregation if the y-axis after grouping is classified data), avoiding invalid exploration. The adaptive random exploration strategy adopts a formula

$$a_i = \begin{cases} randomL(S_i, A_i) & prob\, p_n \\ argmax_{b \in L(S_i, A_i)} Q_i(b) + C \quad 2 \ln t / N_i(b) & prob\, 1 - p_n \end{cases} \quad (Formula\ 2)$$

among them, $p_n = a^n$ decays as the number of clauses n increases, balancing extensive exploration in the early stage and precise utilization in the later stage. Composite reward function

$$R = K_r \cdot (\alpha S_d + (1 - \alpha) S_u) \quad (Formula\ 3)$$

$K_r$is the domain knowledge compliance marker (1/0), S_d is based on data feature scoring (trained from 14 features such as axis data type, correlation, etc. using the LambdaMART model), andS_u is the user preference score (trained on the Plotly dataset using a GAN model, with the generator simulating user behavior and the discriminator distinguishing between generated and real scores). This function integrates data characteristics, domain rules, and user preferences, effectively guiding search direction and improving the diversity and accuracy of recommendation results, supporting efficient and high-quality automated visualization generation.

4. Results and discussion

4. 1. HAIHart Experiment - Analysis of Recommendation Efficiency Driven by Pruning Rewards

This paragraph verifies the effectiveness of the HAIChart system through multidimensional experiments. The experimental setup adopts VizML (including 120000 user generated visualization samples, divided into 7:1:2 training/validation/testing sets, with an average of 2 visualizations per sample) and KaggleBench (including 8 representative datasets, with an average of 31. 5 visualization results per dataset) as two datasets. The KaggleBench sub dataset details. Selection of evaluation indicators Hit@k (Top-k recommendation accuracy), P @ k (accuracy) Rt@k The proportion of Top-k containing the true results of Top-t, specific definition, and k value setting (such as VizML's) Hit@3, KaggleBench's R10@30. Please refer to the experimental instructions for details. As shown in Figure 1 of the single round recommendation effectiveness experiment.

HAIHart's overall performance in VizML Hit@3 The indicator reaches 91. 9% (surpassing PVisRec 24. 8%), which is on KaggleBench R10@30 The indicator reaches 83. 7% (super DeepEye 16. 2%); The comparison methods include advanced methods such as DeepEye (rules+domain knowledge), Data2Vis (sequence to sequence model)[6], PVisRec (user preference driven), etc. HAIChart performs the best. The necessity of verifying optimization strategies through ablation experiments: After removing pruning algorithms, VizML's Hit@3 Decreased by 3. 3%; After removing the random exploration strategy, the P @ 10 of KaggleBench decreased by 9. 6%. The composite reward function ablation experiment shows that removing any dimension of data characteristics/domain knowledge/user preferences leads to a decrease in performance, such as the KaggleBench after removing user preference ratings R10@30 Decreased by 28. 8%. The efficiency experiment was tested on KaggleBench, and HAIChart had an average processing time of 2. 4 seconds (1. 8 times faster than MCTS). In datasets with a large number of columns (such as D3 with 15 columns), the speed was increased by 2. 9 times, meeting the requirements of interactive exploration; The Zomato dataset (51717 data points) has a slightly longer processing time, but it still meets user response requirements through domain knowledge pruning. In summary, the experiment verified the superiority of HAIChart from four aspects: accuracy, effectiveness of optimization strategies, rationality of reward function design, and system efficiency, providing solid empirical support for automated visual recommendation.

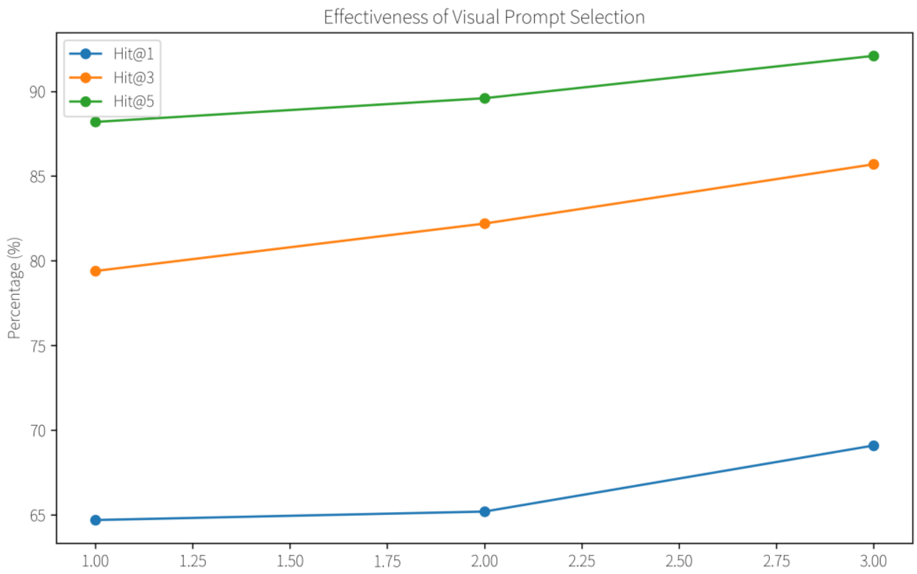

Figure 1 prompts for selecting validity verification

4. 2. Model experiment

To address the issue of existing automated visualization technologies neglecting active exploration of user intent, this chapter proposes a user selection oriented visual recommendation method that guides users to gradually refine their visual intent through simplified interactive prompts. This method introduces a "Single choice question" prompt mechanism to transform the complex decision-making process into user friendly natural language choices (such as "explore by category/time<data field>"), reducing the threshold of use and accelerating data insight acquisition. The prompt corresponds directly to the visualization operation, associating high-value visualization results sorted by the composite reward function, forming a "prompt visualization" mapping. Aiming at the NP hard problem of Top-k prompt selection, a greedy algorithm is designed to solve it in two steps: in the stage of candidate prompt generation, a prompt set is constructed based on the node information of the visualization graph, and a decay coefficient (δ =1/(N_total/N_viz)) is introduced to adjust the weight of repeated visualization scores and avoid redundant results; In the selection stage, first filter out legal prompts with costs (associated visualization quantities) not exceeding budget B, then sort them by average/total score, prioritize high scoring prompts until k are reached or the total cost exceeds the limit, and ultimately maximize the overall reward value under budget constraints. Experimental verification shows that this method effectively integrates user intent, improves the relevance of recommendation results, and enhances user satisfaction.

4. 3. Effect analysis

This paper proposes a visual prompt mechanism guided by the user's choice[7], which simplifies the user's decision-making process through the "Single choice question" type natural language prompt, reduces the threshold of use and speeds up data insight acquisition. The prompt corresponds directly to the visualization operation, associating high-value results sorted by the composite reward function to form a "prompt visualization" mapping. Aiming at the NP hard problem of Top-k prompt selection, a greedy algorithm is designed to solve it in two steps: in the candidate prompt generation stage, a prompt set is constructed based on visualization nodes, and a decay coefficient (δ =1/(N_total/N_viz)) is introduced to adjust the weight of repeated visualization scores; In the selection stage, first filter out legal prompts with costs (associated visualization quantities) not exceeding budget B, then sort them by average/total score, prioritize high scoring prompts until k are reached or the total cost exceeds the limit, and ultimately maximize the overall reward value under budget constraints. The search strategy constrained by user intent guides the search direction through prompts, effectively pruning the search space and improving efficiency. Experimental comparison of HAIChart and Voyager2, effectiveness verified through multiple rounds of interaction: objective indicators (as shown in Table 2)

Table 2 Performance Comparison of HAIChart and Voyager 2 on KaggleBench Dataset

Dataset	Task	Metric	Voyager 2 (Round 1)	Voyager 2 (Round 2)	Voyager 2 (Round 3)	HAIChart (Round 1)	HAIChart (Round 2)	HAIChart (Round 3)
KaggleBench	Data Query	P@10	45. 0%	55. 1%	58. 0%	63. 8%	69. 5%	79. 2%
KaggleBench	Design Choice	P@10	78. 7%	96. 3%	97. 4%	96. 3%	97. 6%	99. 3%
KaggleBench	Overall	P@10	40. 0%	44. 9%	45. 7%	55. 0%	58. 2%	68. 8%

HAIChart has a significant advantage in P @ 10 and recall rate; Subjective evaluation shows that users are more appreciative of their ability to reduce operational complexity. (as shown in Table 3)

Table 3 Experimental Results of Visual Prompt Selection Effectiveness

Dataset	Evaluation Metric	Round 1	Round 2	Round 3
KaggleBench	Hit@1	64. 7%	65. 2%	69. 1%
KaggleBench	Hit@3	79. 4%	82. 2%	85. 7%
KaggleBench	Hit@5	88. 2%	89. 6%	92. 1%

Increase in interaction rounds to drive progress Hit@k Continuous optimization of indicators has confirmed a significant improvement in recommendation accuracy. This method achieves a high degree of consistency between recommendation results and user needs through the synergy of prompt interaction and user intent constraints, optimizing efficiency and accuracy in both directions, and providing a closed-loop solution of "precise adaptation efficient interaction deep insight" for intelligent visual recommendation.

5. Conclusion

This study proposes a data visualization recommendation system HAIChart based on reinforcement learning, which integrates artificial intelligence computing capabilities with user intuitive insights to construct a human-machine collaborative optimization framework [8]. The system adopts a dual module design of offline learning and online recommendation [9], using a large number of visual examples to train the model, and combining real-time user feedback to iteratively optimize the recommendation quality. This framework constructs a new paradigm of intelligent visual recommendation through three breakthroughs: pioneering the modeling of visual generation as a Markov decision process, combining composite reward functions with Monte Carlo graph search to accurately adapt to dynamic demands; Optimize search strategies to improve recommendation efficiency and result accuracy; Design an intelligent prompt mechanism to integrate user intent, guide demand refinement through natural language interaction, and form a closed-loop optimization from demand understanding to personalized recommendations. This path enhances the system's dynamic response capability, deepens user engagement, and achieves a three-dimensional technological breakthrough of "decision modeling strategy optimization interaction guidance". Experimental verification shows that HAIChart is significantly better than existing tools in terms of recall rate, exploration efficiency, and user satisfaction, such as the VizML dataset Hit@1 Reaching 79. 3%, the KaggleBench data query task P @ 10 increased to 79. 2% in the third round. Future research directions focus on multimodal interaction extension (such as speech/gesture recognition), real-time visualization support for dynamic data [10], enhanced interpretability of artificial intelligence decisions, and performance optimization in large-scale data scenarios, aiming to promote the development of more intelligent and transparent visual recommendation systems and expand the application potential of mobile devices, virtual reality, and other scenarios.

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