Business Intelligence Implementation in the Framework of Enhanced Learning Application

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ABSTRACT: In view of the large data background, this paper discusses the application scheme and related technology of enhanced learning in business intelligence in machine learning method. By using reinforcement learning algorithm, aiming at the characteristics of business intelligence system in large data scenarios, this paper explores the construction method and application process of business intelligence system with reinforcement learning. This paper improves the traditional business intelligence system concept, collaboratively applies large data analysis technology and reinforcement learning method in machine learning field to solve the real-time analysis and calculation problems that restrict future intelligent systems, and improves the decision-making level and efficiency of enterprises.

1. Overview of Business Intelligence
The definition of Business Intelligence (BI) was first proposed by Howard Dresner, a researcher at Goldner Consulting Company. He believes that BI is a means of assisting business decision-making by applying fact-based support systems, and it is a concept and method. This definition has been accepted by many researchers. However, with the cross-cutting of multidisciplinary knowledge and the improvement of the relevance of various technologies, data warehouse, data mining, machine learning and other technologies have their corresponding applications in business intelligence, and academic views on business intelligence have been controversial. It mainly focuses on whether it is a new advanced information system or a part of the traditional data-driven decision support system. The emergence of business intelligence is not accidental, it is the inevitable result of the expansion of enterprises and the whole development process. With the development of information technology, the changing market environment and customer demand, the competition between enterprises is becoming more and more fierce, and business intelligence is also developing continuously.

2. Application of Business Intelligence
Business Intelligence System (BIS) is a multi-disciplinary analysis and decision-making system. The data it obtains are different types of data from different data sources. Through these technologies, enterprises can quickly find hidden information in complex business environment, thus improving the accuracy and efficiency of enterprise decision-making and enterprise prediction. Generally speaking, the value of Business Intelligence to today's companies is as follows:
(1) Efficient analytical ability. At present, most companies rely on information for their development. When the information reaches a certain level, it is necessary to analyze the information of suppliers, manufacturers, sales markets and customers. This process is the application of business intelligence. Through the Business Intelligence Platform, the implicit information of these data can be quickly analyzed, so that the company's decision makers can better grasp the operation of the
enterprise and solve the current problems of the company. Therefore, Business Intelligence (BI), an efficient analytical capability, plays a vital role in the whole operation of a company.

(2) Improvement of decision-making efficiency and level. As mentioned earlier, business intelligence systems can quickly analyze and integrate historical information to enable decision makers to understand the operation status. However, the multi-disciplinary and multi-technology cross-cutting analysis system of business intelligence can process these information more deeply and transmit it to the users who need it at the appropriate time, so as to help decision-makers make decisions quickly and improve the accuracy of decision-making.

(3) Bring high income to the company. Companies aim at operating profits, hoping to get the highest profits at the lowest cost. In the process of business intelligence operation, a lot of hidden information has been excavated, which not only saves the cost of human information analysis, but also improves the efficiency of analysis. Therefore, more and more enterprises now want to have business intelligence systems.

3. Implementing Business Intelligence in Enhanced Learning

This paper mainly studies the realization of Business Intelligence based on Enhanced Learning. For any learning model, it has its own environment definition. Combining with the research questions in this paper, the environment in this paper can be divided into a limited number of states, and there are some links between these states, so that they can be transformed into each other in some ways. Mainly used to solve the problem of business intelligence with Markov and result lag, to help enterprises make optimal decisions quickly.

3.1 Model Construction

At present, some business intelligence problems with Markov and result lag can be solved by reinforcement learning method. Therefore, this paper constructs an environment learning model of business intelligence by introducing reinforcement learning method and using MDP. Based on historical data, an intelligent learning system is simulated, which enables the system to quickly learn the learning path when it reaches the optimal decision-making state.

According to Markov decision process theory, its composition can be seen as a quintuple \( \langle S, A, P, R, \gamma \rangle \).

- \( S \) is a finite state set
- \( A \) is a finite action set.
- \( P \) is a state transition probability matrix. \( P_{s_s}^a = P[S_{t+1} = S'|S_t = S, A_t = a] \)
- \( R \) is a reward function. \( R_s = E[R_{t+1}|S_t = S, A_t = a] \)
- \( \gamma \) is a discount factor. \( \gamma \in [0,1] \).

Business intelligence problems are the same. First of all, these problems need to be solved have clear boundaries. Through its characteristics, limited states can be divided, and states can be transformed. For specific business intelligence problems better explanation. For example, we choose the inventory problem in business intelligence, \( S \) represents the state (inventory can be divided into state sets), constitutes the state set; \( A \) represents a group of actions (e.g., adjusting inventory to increase or decrease it), action \( A \) controls the transition between states. \( p_{sa}^a \) is the probability of state transition, which indicates the probability distribution of other states that will be converted to when the action of \( a \) is taken under the current state \( s (s \in S) \). \( \gamma \in [0,1] \) is the discount factor. \( R = f(s, a) \), \( R \) is the reward function, reward function is often expressed \( R = f(s) \) (only related to \( S \)). The learning system environment of reinforcement learning forms part of reinforcement learning, and then reinforcement learning related methods are adopted to solve some problems in business intelligence for the constructed system.
3.2 Implementation process

(1) The state partitioning problem in business intelligence can be partitioned according to the actual situation, using polymorphic Markov theory to partition their states. Generally, if a business intelligence problem involves fewer states, it can be divided artificially, but in the case of more states, it can be divided by machine learning method. The partition of States is generally expressed by S. For business intelligence problems, we divide the relevant data into N States after analysis, and $S_i$ represents state i, where $i = 1, 2, 3, \ldots, N$. Of course, there are many methods to classify states, but they can generally be divided into existing criteria or subjective consciousness to classify states, sample mean - standard difference classification, clustering analysis, and state partition based on Simulation values. In data processing of business intelligence, these methods can also be used to divide a large number of data into states, in order to solve the problem of large amount of data and data information disorder.

(2) Specific solution process

Some relationships can be established between states, which can be represented by the MDP process. After converting to the dynamic process of MDP, the reinforcement learning method is selected according to the specific problems in the process of implementation, which makes the whole process more convenient and faster. The steps of MDP generally have the following aspects: First, suppose that $S_0$ is the initial state of Agent, then select an action to run randomly in action set $A$. After running, Agent will transfer from the current state (Markov decision according to probability, enhanced learning is not needed) to the next state $S_1$, then repeat the previous step, select an action to start running, and run. Then go to the next state $S_2$ and repeat the steps. The specific process is as follows:

$$S_0 \rightarrow S_1 \rightarrow S_2 \rightarrow S_3 \rightarrow \ldots$$

Definition: After executing the entire transfer path above, the sum of return functions can be obtained as shown in formula (3.1):

$${(3.1)} \quad R(s_0,a_0) + \gamma R(s_1,a_1) + \gamma^2 R(s_2,a_2) + \ldots$$

The ultimate goal of an agent is to obtain a set of optimal strategies, which weights the returns and maximizes expectations.

$${(3.2)} \quad E[R(s_0) + \gamma (s_1) + \gamma^2 R(s_2) + \ldots]$$

As can be seen from formula (3.2), the return value in the second state is discounted by $\gamma^1$, which is similar to a process of gradual weakening. The more advanced the state is, the greater the impact on the return will be, and the less backward it will be.

In reinforcement learning, when Agent is in the current state $s$, the next action $a$ is selected according to a strategy $\pi$, and then changes to the next state $s'$. The process of choosing action is usually called strategy (policy in reinforcement learning elements). Each strategy reflects a state-to-action mapping function, i.e. $\pi : S \rightarrow A_s$. The given policy function $\pi$ is equivalent to the action that should be performed in a given step in each state.

Generally, to measure the quality of strategy $\pi$, we need to judge the result of strategy execution by introducing a value function or discounted cumulative reward.

$${(3.3)} \quad V^\pi (s) = E[R(S_0) + \gamma (S_1) + \gamma^2 (S_2) + \ldots | S_0 = S, \pi]$$

Formula (3.3) shows that the expectation of the weighted sum of returns equals to the value function when the starting state $s$ is arbitrarily obtained and the strategy is selected. This process is similar to the process of applying enhanced learning to chess introduced earlier. If the current chess game is set to $S_0$, there will be many kinds of Walker schemes, which are what we call action strategy $\pi$. The evaluation of all action strategy schemes is based on its future situation $(R(s_1), R(s_2), \ldots)$ Judgment. Although we will think more about the next few steps in our mind when we take each step in the whole chess game, we will generally pay more attention to the situation of the next step.
Value function is generally expressed as follows: the determination of action strategy $\pi$ is equivalent to knowing the next plan. This plan usually goes through many states, and each state will have its corresponding reward value. The closer the other states are to the current state, the greater the effect, and the higher the weight value. According to the principle of recurrence, the value function $V$ of the current state $s$ is equal to the reward $R(s)$ of the current state plus the value function $V'$, that is, the formula (3.3) can be written as formula (3.4):

$$V^\pi(s) = R(s_0) + \gamma(E[R(s_1) + \gamma(s_2) + \gamma^2(s_3) + ...])$$

However, we still need to pay attention to the fact that when the action strategy $\pi$ is given, even if we know that its action $a$ is unique under state $s$, the mapping from these actions to the latter state is not necessarily unique. For example, if you choose action $a$ to toss a coin up, there may be two situations for its next state. So Bellman's equation is derived from the above equation:

$$V^\pi(s) = R(s) + \gamma\sum_{s'\in\mathcal{S}_s}P_{s\pi}(s')V^\pi(s')$$

$s'$ is recorded as the next state. The former $R(s)$ is called immediate reward, which is $R$ (the current state). The second expression can also be written as $E_{s\rightarrow psn(s)}[V^\pi(s')]$, which indicates the expectation of the next state value function and the next state $s'$ conforms to the $P_{s\pi}(s)$ distribution.

Observing the whole process, we can see that the defining value function $V$ of each state $s$ can be obtained by formula (3.5). (There is no second term $V(s')$ in the final state.) It can also be obtained directly by solving linear equations.

The purpose of finding out each state $V$ is to find out the optimal action strategy $\pi$ under the current state $s$. Here we define the optimal $V^\star$ such as (3.6):

$$V^\star(s) = \max V^\pi(s)$$

(3.6)

Represents the selection of an optimal policy from the policy set $\pi$.

Finally, Bellman’s optimal strategy equation is written in the following form:

$$V^\star(s) = R(s) + \max \sum_a p_{sa}(s')V^\star(s')$$

(3.7)

The first term has nothing to do with $\pi$, so it doesn’t change. The latter item indicates that the next action $a$ of each state $s$ is determined by the $\pi$ strategy. After executing $a$, $s'$ returns probability and expectation in probability distribution.

Define the best definition value function $V^\star$, and then define an optimal strategy $\pi^\star: S \rightarrow A$ as follows:

$$\pi^\star(s) = V^\pi^\star(s) \geq V^\pi(s)$$

(3.8)

By choosing the best strategy $\pi^\star$, the next best action $a$ of each state $s$ is obtained. According to formula (3.8), we can know that

$$V^\star(s) = V^\pi^\star(s) \geq V^\pi(s)$$

(3.9)

Formula (3.9) shows that the optimal value function $V^\star$ of the current state can be obtained according to the optimal execution strategy $\pi^\star$. The return of the optimal strategy must be higher than that of any other strategy $\pi$. Overall, the mapping relation of state $S$ taking action $A$ can be achieved, and this mapping is the best one, called $\pi^\star$. For the state set $S$ of the whole learning system, as long as the next action $a$ of each state $s$ is determined, it will not change because of the different selection of the initial state $s$.

4. Summary

The application framework of Business Intelligence based on Enhanced Learning provides a concrete solution to the problem of Business Intelligence with Markovian, lagging results and limited state partition. Through the analysis of the construction of learning model, the solution of value function and the method of strategy evaluation by Markov decision-making, the complete process of enhancing learning to solve business intelligence problems is shown.
Reference

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