Research on Particle Swarm Practical Algorithm of Partial Differential Exact Solution Based on Computer Software Analysis

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Abstract. Particle swarm collaboration has many applications on the Internet. It is necessary to cluster a large number of algebraic matrices to obtain enough data. The current research focuses on the correlation between particle swarm coordination and matrix, and does not fully consider the difference between geometries. There is a large overlap, which leads to the same results for different matrices, leading to double counting problems. Therefore, based on the analysis of computer technology, this paper proposes a particle swarm optimization algorithm based on partial differential exact solutions. The selected geometric matrix has higher correlation and lower overlap. Experimental results show that this method can significantly improve the accuracy and efficiency of particle swarm coordination.

Key words: Partial Differential, Exact Solution, Particle Swarm Practical Algorithm, Computer Software

1. Introduction

At present, the research on particle group synergy and practicalization focuses more on the related precise clustering. In this method, the correlation between the algebraic matrix and the particle swarm is analyzed, and the database digest is used to realize this estimation [1-3]. At present, there are research methods: sampling methods and methods for maximum entropy implementation. Using the method of sampling, the method is aimed at the static Top-K precision clustering method, which mainly utilizes the partial differential exact solution method. In this way, the number of tuples with different results is determined by the determined K algebraic matrices [4, 5]. In this paper, the partial differential exact solution is mainly analyzed, and try to obtain as many results as possible by the smallest possible matrix cost to achieve the practical effect of the particle group. And combined with the shortcomings in the current work, that is, the analysis of statistical data is only partial statistical data. In this paper, in order to effectively deal with the overlapping precision clustering method, a method of partial differential exact solution at the tuple level is proposed.

2. Partial differential exact solution of particle swarm practical algorithm
(1) Partial differential exact solution

Although the current partial differential differential solution method can effectively confirm the
hierarchy through the attribute value domain, there is no way to achieve random sampling in this method. Therefore, the error of the clustering result is difficult to be effectively controlled. Therefore, this paper solves the problem of particle group synergy practicalization by establishing a partial differential exact solution.

Assume that \( d \) is a given matrix at this time, in which there are tuples \( |d| \), corresponding attributes are \( n \), that is, \( A = \{ A_1, A_2, \cdots, A_n \} \) and \( \Phi \subseteq A \) represent hierarchical attribute sets, and for tuples of \( d \), \( d(\Phi) \) represents values corresponding to \( x \) on \( \Phi \). Different sets, therefore, each \( c \) has a corresponding tuple set belonging to \( d \), namely, \( d(x) = \{ t : t \in d \} \). Moreover, on the set \( \Phi \), \( t \) takes a value equal to \( x \}, \) and \( |d(\Phi)| \) represents the number of packets that the attribute set \( \Phi \) has.

A. Determine the sampling level \( \Phi \): For the selection of the hierarchical attribute set, it can be set in advance. It can also be determined by methods such as decision trees. Combining the information gain to achieve efficient ordering of attributes, for example, for attribute \( \Phi \), the entire level \( \{ x_0, \cdots, x_{|d(\Phi)|} \} \) can be obtained using the attribute value field.

B. Determine the sample size \( N_s \) for each layer: when \( x \in \{ x_0, \cdots, x_{|d(\Phi)|} \} \), \( d(x) \) cluster \( Q \), confidence \( 0 < \delta < 1 \), construct the indication function: take tuple \( t_i \in d(x) \), if \( t_i \in Q(d(x)) \), \( y_i = 1 \); otherwise, \( y_i = 0 \). Then \( \Pr[Y_i = 1] = p = \frac{|\Omega(d(x))|}{|d(x)|}, \) \( \Pr[Y_i = 0] = 1 - \frac{|\Omega(d(x))|}{|d(x)|} \), then \( Y_i, \cdots, Y_{N_s} \) is an independent Poisson observation, let \( \bar{Y} = \sum_{i=1}^{N_s} Y_i \), \( \mu = \mathbb{E}[\bar{Y}] = N_s p \), for any given relative error \( \varepsilon > 0 \), by Chernoff Bound:

\[
\Pr\left[|\bar{Y} - \mu| \geq N_s \varepsilon \right] \leq 2 \exp\left(-N_s \varepsilon^2 / (2 + \varepsilon)\right) = 1 - \delta
\]  \( (1) \)

Therefore, the level determines the number of samples to be extracted as:

\[
N_s = \min \left\{ \left[ \frac{2 + \varepsilon}{\Omega(d(x))} \frac{1}{\varepsilon^2} \ln \frac{2}{1 - \delta} \right] \left[ \frac{\Omega(d(x))}{|d(x)|} \right] \right\}
\]  \( (2) \)

(2) Particle swarm collaborative clustering

Particle cluster co-clustering is difficult to overlap between particle swarms. Therefore, based on sample estimation, this paper analyzes the overlap rate of two particle swarms, as shown in Figure 1:
Figure 1. Overlay rate estimation for complete samples.

The first one is a method based entirely on sample implementation. Specifically, samples between different particle swarms can be used to estimate the overlap ratio of each other. In the case of Figure 1, sorting according to the size of the coverage, \( C(d_1) > C(d_2) > C(d_3) \) can be obtained. when making a choice, consider cluster \( d_1 \) in the first place, \( d_2 \) or \( d_3 \). The basic principle that should be adhered to when making choices is that the coverage rate is the best. The requirement to measure the size of \( |Q(d_2) - Q(d_1)| \) and \( |Q(d_3) - Q(d_1)| \) is based entirely on the sample strategy: for the number of overlapping tuples in the original particle swarm, it can be estimated by overlapping tuples in the sample.

In this method, an effective estimation of the overlap ratio is achieved by comparing the un-clustered and the clustered particle swarms. Also sorting according to its repetition rate, it is possible to derive \( C(d_1) > C(d_2) > C(d_3) \), and it is necessary to estimate the sizes of \( |Q(d_2) - Q(d_1)| \) and \( |Q(d_3) - Q(d_1)| \) to select the particle group with the largest remaining coverage. We have obtained \( Q(d_1) \) and estimate the number of overlapping tuples in \( Q(d_1) \) and \( Q(d_2) \) by comparing the same tuples of \( Q(d_1) \) and \( Q(S(d_2)) \):

\[
O(Q(d_1), Q(d_2)) \approx \frac{|Q(d_2)| \times |Q(d_1) \cap Q(S(d_2))|}{|Q(S(d_2))| \times |Q(\Omega)|}
\]  

(3)

\(|Q(d_i)| (i = 1, 2)\) can be obtained by using the sample \( S(d_i) \) and the formula (4), and \( |Q(d_2) - Q(d_1)| \) can be estimated by the formula (3), whereby the size of \( |Q(d_1) - Q(d_i)| \) can be further estimated. At this point, it is necessary to perform a sample analysis on a particle swarm to achieve an effective estimation of the number of overlapping tuples, and when the number of samples is sufficient, the accuracy obtained will be more accurate, and thus obtain the following theorem.

3. Experimental results and analysis

(1) Experimental preparation

The TPC-W data set \( z \) can use the TPC-W benchmark to obtain 97,761 different tuples, which are stored in the relational table Book. And they are divided into 100 particle groups, each of which will
be randomly assigned to 1-20 particle groups using Zipf distribution, and the corresponding parameters are set to \( z=1 \). Table 1 shows the specific particle swarm statistics, in which the hierarchical attributes with larger discriminant degree are selected, that is, pubyear and subjecto use the cluster of online bookstores to obtain the average connection time range of the particle group. Between 200 and 800 milliseconds, the corresponding transmission time of a single tuple is 0.3 milliseconds. In the experiments conducted in this paper, the confirmation of the particle group connection and transmission time is realized based on these data. Moreover, after observing the online bookstore page, the parameter \( \text{topK}=20 \) is set.

Sampling method: In the experiment, there are three main algorithms for analysis, namely, main sampling method, simple random sampling, cluster-oriented partial differential exact solution and tuple-oriented partial differential exact solution method. And a sample table is constructed, in which the segment sampling probability sampleratio and the particle group sourceid are added thereto compared with the Book table.

(2) Statistical accuracy comparison

It should be clear that if the sampling based on clustering is difficult to obtain the potential data distribution, then the analysis of the clustering error on the sample is difficult to achieve. Therefore, this is the case. In the experiments in this paper, the sampling ratios taken for each particle group are different (Table 1).

Table 1 summarizes the number of clusters required to obtain the same proportion of samples without the sampling method. Analysis can be obtained: In contrast, the method for partial differential exact solution requires the least number of clusters: but as the number of samples increases, the number of clusters is also increasing. It should be clear that: (1) Under the 7.5% and 10% samples, the same number of clusters is required to use the partial differential exact solution method. Because, at this time, the cluster tuples of each layer are on the same page; (2) because the "drill down" is required, the number of clusters required by the simple random sampling right method is more, but the other two methods increase the number of samples. When the results are getting closer and closer. Because both methods are tuple selection from the reverse side.

| Sampling method                                      | 5%  | 7.5% | 10%  | 12.5% |
|-----------------------------------------------------|-----|------|------|-------|
| Simple random sampling                              | 13438 | 21103 | 29647 | 39181 |
| Partial differential exact solution for tuple       | 7099  | 8519  | 8519  | 11359 |
| Partial differential exact solution for clustering  | 8645  | 9496  | 10175 | 11381 |

4. Conclusion

Under the analysis of computer software, this paper proposes an exact differential solution method based on partial differential to estimate and use the clustering information to the effect of particle swarm synergy. The selected particle swarm has higher correlation and lower overlap. The specific implementation steps of the method are as follows. In the offline phase, it is necessary to obtain an accurate partial differential solution to obtain the required sample data: in the online phase, the sample data is iteratively estimated, and the sample data is iteratively estimated with degree and overlap ratio. In addition, the algorithm also obtains a lower overlapping particle swarm through heuristic strategies, and conducts actual data experiments. Experimental results show that this method not only can effectively meet the practical application of particle swarms, but also greatly improves the efficiency.

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