Adapted Extremal Optimization
For Materialized Views Selection

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ABSTRACT
With the development of databases in general and data warehouses in particular, it is now of a great importance to reduce the administration tasks of data warehouses. The materialization of views is one of the most important optimization techniques. The construction of a configuration of views optimizing the data warehouse is an NP-hard problem. On the other hand, the algorithm called extremal optimization is used to solve complex problems. In this paper, we propose a new adapted extremal optimization (AEO) for the materialized views selection problem.

2. ART STATE
In this section we represent an art state study about the Bak-Sneppen model, the extremal optimization algorithm, the AND-OR view graph and the materialized view selection.

2.1 Bak-Sneppen Model
The Bak-Sneppen model [1] is a model of evolution between species. Its major characteristic is that it considers the whole ecosystem and the co-evolution of many different species rather than focusing on single species.

A “fitness” value between 0 and 1 associated to the species which are located on the sites of a lattice (or graph. At each time or step (iteration), the one species with the worst fitness (poorest degree of adaptation) is selected to be updated randomly, having its fitness replaced by a new random value drawn from a flat distribution on the interval [0, 1]. This corresponds to the natural process of species’ development or where a species is replaced by another one. In food chain for instance, the no species lives alone but depends on its successors and predecessors. Bak and Sneppen consider this by arranging the species in a one dimensional line. If one species is mutated, the fitness values of its successors and predecessors in that line are also set to random values [1].

Therefore, all of the species connected to the “weakest” have their fitness affected (replaced by new random numbers as well). After a sufficient number of iterations, the system reaches a highly correlated state known as self-organized criticality (SOC) [2]. Almost all species have reached fitness above a certain threshold. These species possess punctuated equilibrium [3]: only one’s weakened neighbor can weaken one’s own fitness.

2.2 Extremal Optimization
EO is an evolutionary meta-heuristic oriented local search proposed by Boecher and percus [4], [5], [6], [7] inspired from statistical physics and the model of co-evolution between species in order to find high quality solutions for hard problems.

As in Bak-Sneppen model, EO merely updates those variables having an extremal (worst) arrangement in the current configuration, replacing them by random values without any improvement of their performance. Large fluctuations allow escaping from local optima.

In order to make EO easier and more understandable, we will compare it with another well-known method such as the genetic algorithms (GA) [8]. First, a GA has a set of parameters to be
tuned like the size of population, probabilities of reproduction and number of generations; however, in EO there is only one parameter to be tuned. Second, in EO the fitness value is not calculated for each structure that represents a solution (individual or chromosome) as in a GA but for each component of the structure which is represented by a species; each species is evaluated according to its contribution in obtaining the best solution. Third, EO works with a single solution instead of a population of solutions as in GA. Last, EO replaces the worst components for the next iteration; in contrast, GA promotes a group of elite solutions.

As it is mentioned above, EO has only one species parameter that is often referred to as \( \tau \) [9]. This parameter is used probabilistically to choose the component value to be mutated at each iteration of the algorithm. The algorithm ranks the components and assigns to them a number from 1 to \( n \) using the fitness of each one (where \( n \) is the number of components). Therefore, the fitness must be sorted from the worst to the best. The probability is calculated as follows:

\[
P_i = \frac{i}{\tau} 
\]
\( \forall i \leq i \leq n \tau \geq 0 \)  

Where:
\( n \) is the total number of components evaluated and ranked, and \( P_i \) is the probability that the \( i^{th} \) component is chosen.

The problem of materialized views selection is the construction of a configuration of views in optimizing the execution cost of a data load. This optimization may be realized under certain constraints such as the storage space allocated for selected views or a superior boundary of the views maintenance cost [11]. We consider the first constraint by the rest of the paper.

Let \( CV \) be a set of materialized views that are qualified to be candidates to reduce the execution cost of queries set \( Q \), generally supposed to be representatives of the system load. Let \( S \) be the disc space allocated by the administrator of the data warehouse for the creation of views. The problem of MVS is to construct a configuration of views \( V \subseteq CV \) minimizing the execution cost of \( Q \), under the constraint of space. The problem can be formalized as follows:

\[
\sum_{v \in V} \text{taille}(v) \leq S
\]

Many materialized view selection algorithms have been proposed to deal with this problem, such as greedy heuristic algorithm [12] and GA [13], but these algorithms have some limits. The greedy heuristic algorithm is highly problem dependent whereas in GA, it is hard to acquire good solutions in the beginning (first iterations).

### 2.4 Graph AND-OR For MVS

A graph \( G \) is called AND-OR view graph (figure 1) for the views (or queries) \( v_1,v_2,\ldots,v_k \), if for each \( v_i \) there is a sub-graph \( G_i \) in \( G \) which is an expression AND-OR-direct acyclic graph (AO-DAG) for \( v_i \) [14].

Each node \( u \) in an AND-OR view graph has the following parameters associated with it:

- \( f_u \): frequency of the queries on \( u \).
- \( s_u \): space occupied by \( u \).
- \( g_u \): frequency of updates on \( u \).

Given set of queries \( q_1,q_2,\ldots,q_k \) to be supported at a data warehouse, the AND-OR view graph can be constructed in terms of the following steps: The first step is to construct the expression AO-DAG \( d_i \) for each query \( q_i \), then, we combine all the expressions AO-DAG \( d_1,d_2,\ldots,d_k \) in order to obtain an AND-OR view graph \( G \) for the set of queries. Each view is presented by a node of the graph in relation with a query intensive nature.

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Each view is presented by a node of the graph in relation with a group of views it needs in order to be calculated; there is an AND relation between the views of the same group which is represented by the arc in figure 1. The relation OR can be between two or more groups of views indicating that the views can be calculated from any group of them. For instance, in figure 1 the view (a) can be calculated from the views (b, c and d) or (d, e and f).

In short, given an AND-OR view graph \( G \) and an available space size quantity \( S \) provided by the data warehouse, the materialized view selection problem aims to select a set of views \( V \) (i.e., a subset of the nodes in \( G \)), which minimizes the sum of total query response time and total maintenance cost, under the constraint that total space occupied by \( V \) is less than \( S \).
3. ADAPTED EO FOR MATERIALIZED VIEW SELECTION

Algorithm 2: AEO pseudo-code for materialized views selection.

Generate an initial random solution \( V = (v_1; v_2; \ldots; v_n) \) where \( \sum_{i=1}^{n} \text{size}(v_i) \leq S \)

\[ V_{\text{best}} \leftarrow V; \]

For a preset number of iterations do

1. Evaluate and rank fitness \( \lambda_i \) for each \( v_i \) from worst to best;
2. Generate the probabilities array \( P \) according to Equation 1;
3. \( j = \) Select component based on the probability of its rank \( P_i \);
4. \( v_j = \) Generate a random appropriate value that is not equal to \( v_j \); where \( \sum_{i=1}^{n} \text{size}(v_i) \leq S \)
5. \( \text{Eva}(V) = \) Evaluate the new solution;
6. if \( \text{Eva}(V) < \text{Eva}(V_{\text{best}}) \) then \( V_{\text{best}} = V; \)

end for

Return \( V_{\text{best}} \) and \( \text{Eva}(V_{\text{best}}) \);

Since the materialized view selection problem has been proved to be NP-hard [15] it is impossible to resolve this problem by using the traditional algorithms. In this section, we propose a meta-heuristic algorithm called adapted extremal optimization (AEO) to deal with this problem using the extremal optimization (EO) method.

As it is mentioned above, the extremal optimization receives only one parameter \( \tau \), but since our problem is constrained we have to adapt the algorithm to make it receive our space constraint as a new parameter.

The first step of our adapted algorithm is to generate a random solution composed of a certain number of species (views or queries); this number is limited by the disc space S. The relation between the views is materialized in a graph AND-OR, the view graph is encoded as a binary string, where the constant number is the number of candidate views in the AND-OR view graph, the bit 0 denotes the corresponding node (view/query) is not materialized in the warehouse, the bit 1 denotes the corresponding candidate node (view/query) in the AND-OR view graph is materialized.

The second step is the calculation of fitness: The fitness is the contribution of each species (view or query) in the solution; we simulate our problem to the graph bi-partitioning problem where it is supposed to minimize the relation of the species with the partition’s neighborhood [5] but in our case, we need the opposite i.e. we need to maximize the number of relations between the selected species (views or queries) with the unselected ones. We say that \( v_1 \) is in relation with \( v_2 \) if \( v_1 \) is used to calculate \( v_2 \). If only \( v_1 \) is used to calculate \( v_2 \), then the relation is unique for example we can calculate (e) using only (k); the relation is direct if there is no intermediate views between \( v_1 \) and \( v_2 \);

Each relation has its characteristics; each characteristic has its own coefficient. According to the relation’s characteristics (direct, unique with presence of mates or unique with absence of mates) we multiply the appropriate coefficients to each other:

1. The coefficient is 1 if the relation is direct and unique.
2. If the relation is indirect, the coefficient is \( \frac{1}{NIV + 1} \); where NIV is the number of intermediate views.
3. If the relation is not unique, the coefficient is \( \frac{1}{NVM + 1} \); where NVM is the number of view’s mates.
4. If there is absence of some of the view’s mates (unmaterialized); the coefficient is \( \frac{1}{NAM + 1} \); where NAM is the number of absent mates.

Example 1: in figure1, suppose that the colored nodes compose the initial solution. Table1 explains how to calculate the number of relation of each species according to their characteristics.

Using the number of relations calculated as in table1, we calculate the fitness according to the equation 2:

\[ \lambda_i = \frac{\text{nb}_i}{\text{nb}_p} \]  
(2)

Example 2: \( \lambda_0 = \frac{1}{9} = 0.011 \)

The third step is to rank the species according to their fitness from the worst to the best and replace the worst species (view) with a random one;

The fourth step is to evaluate the new solution; if it is better than the best then it becomes the best;

This process is repeated as desired i.e. according to a preset number of iterations (convergence).
5. CONCLUSION AND FUTURE WORKS
The selection of materialized views is one of the most important problems in the design of data warehouses. Its aim is to find the best configuration of queries where the analyzing cost has to be minimal.

In the next step, we will prove the efficiency of our algorithm by creating a tool based on it and test it on a benchmark.

Since multi-agent systems are favorable to interest the complex system, we will propose multi-agent architecture for our tool.

6. REFERENCES