2.

SUB-COLUMN DETERMINATION ALGORITHM WITH PARTICLE SWARM OPTIMIZATION

The Sub-column determination problem is essentially one of bit width β search. Our proposed algorithm is a cost-modelbased algorithm to find optimal bit width of sub-columns. The unique challenges specific to this problem is to find optimal storage cost of sub-columns with less compression time. We replace the exhaustive search for the optimal subcolumn bit width with a Particle-Swarm-Optimization (PSO) based procedure in Algorithm 4. In Lines 4-9, algorithm initial *i*-th particle's position p_i , its velocity v_i , the best *i*-th position $p_{best,i}$, the minimum cost $Cost_{\min,i}$, the global best position p_{best} , and the global minimum cost C_{\min} . Then, after t_{\max} iterations, the algorithm updates the minimum cost for each particle and the global minimum cost. Particles update their velocities and positions using the standard PSO rule with inertia w and cognitive/social coefficients c_1 , c_2 in Lines 12-13. The global minimum cost C_{\min} is updated whenever any particle finds a lower cost in Lines 14-18. Finally, in the vicinity of the optimal solution β' found by the global search of PSO, another local refinement is performed in Lines 19-23.

Since Algorithm 4 updates s particles with $t_{\rm max}$ iterations, the total runtime is approximately $s*t_{\rm max}*n$ and the time complexity is O(n). The parameters s and $t_{\rm max}$ could be tuned to trade off computational cost against solution quality, which influences compression ratio. This method requires far fewer time cost evaluations than a full exhaustive search for large M in Algorithm 1, when $s*t_{\rm max}$ is far smaller than M.

PROOF OF SUB-COLUMN DETERMINATION PROPOSITION

Proposition 1. For bit width $b_{\beta}(j)$ of j-th sub-column $\pi_{j}(x_{i})_{\beta}$ after bit-packing, we could get

$$b_{\beta}(j) = b_{\beta-1}(j') + \eta(\theta),$$

where $\theta = \beta j$ and $j' = \frac{\theta}{\beta - 1}$.

Proof. When j' is $\frac{\theta}{\beta-1}$, we could conclude that $(\beta-1)j'$ equals to θ and j'-th sub-column (with $\beta-1$) is the front $(\beta-1)$ bits of j-th sub-column. If $\eta(\theta)$ is 0, i.e., θ -th bits in all the values are 0, the bit width of j-th sub-column is that of j'-th sub-column (with $\beta-1$) after bit-packing encoding. \square

Proposition 2. For the given X, if β' is divisible by β , the sub-column cost with bit-packing of β is smaller,

$$BPE(X, j, \beta') \ge \sum_{k=1}^{q} BPE(X, jq + k, \beta),$$

where $\beta' = q\beta$, and q is a positive integer.

Proof. For the given series $X = (x_1, \ldots, x_i, \ldots, x_n)$ and the sub-columns with β' are

$$(\pi'_m(X)\ldots\pi'_i(X)\ldots\pi'_1(X))_{\beta'},$$

Algorithm 4: Sub-column Determination with PSO

Input: Series $X = (x_1, x_2, \dots, x_n)$, PSO hyperparams: swarmSize s, maxIter t_{max} , inertia w, cognitive coefficients c_1 , social coefficients c_2 , localRadius R**Output:** Bit width β' 1 $M = \lceil \log(x_{\text{max}} - x_{\text{min}} + 1) \rceil$; 2 for $i \leftarrow 1$ to s do $p_i = U(1, M)$; $v_i = U(-(M-1)/2, (M-1)/2);$ $Cost_{\min,i} = Cost(X, round(p_i));$ $7 p_{best} = \arg\min_{i} Cost_{\min,i}$; 8 $C_{\min} = \min Cost_{\min,i};$ 9 $v_{max} = M$; 10 for $t \leftarrow 1$ to t_{\max} do for $i \leftarrow 1$ to s do $r_1 = U(0,1), r_2 = U(0,1),$ $v_i = w \cdot v_i + c_1 r_1 (p_{best,i} - p_i) + c_2 r_2 (p_{best} - p_i),$ clamp v_i to $[-v_{\max}, v_{\max}]$; $p_i = p_i + v_i$, clamp p_i to [1, M]; 13 $\beta = round(p_i);$ 14 if $C(X,\beta) < p_{best,i}$ then 15 $Cost_{\min,i} = C(X,\beta), p_{best,i} = p_i;$ 16 if $C(X,\beta) < C_{\min}$ then 17 $C_{\min} = C(X, \beta), p_{best} = p_i;$ 18 $\beta' = round(p_{best});$ 19 20 for $b \leftarrow \beta' - R$ to $\beta' + R$ do if $1 \le b \le M$ then 21 if $Cost(X, b) < C_{min}$ then 22 $C_{\min} = Cost(X, b), \ \beta' = b \ ;$ 23

then $\pi_j(X)$ is $(\pi_{jq}(X)\pi_{jq-1}(X)\dots\pi_{jq-(q-1)}(X))$. Then, the difference ΔC between the sub-column cost with bit-packing encoding of β and β' is,

$$\Delta C = (BPE(X, j, \beta') - \sum_{k=1}^{q} BPE(X, jq + k, \beta))n$$

$$= ((\lceil \log(\max_{1 \le i \le n} \pi'_j(x_i) + 1) \rceil)$$

$$- \sum_{k=1}^{q} (\lceil \log(\max_{1 \le i \le n} \pi_{(j-1)q+k}(x_i) + 1) \rceil))n$$

 $\begin{array}{l} \text{If} \ \max_{1 \leq i \leq n} \pi_{(j-1)q+l_j}(x_i) \text{ is } 0 \text{ and } \max_{1 \leq i \leq n} \pi_{(j-1)q+h_j}(x_i) \text{ is not} \\ 0 \text{ with } l_j > h_j, \text{ we could conclude } \lceil \log(\max_{1 \leq i \leq n} \pi_j'(x_i) + 1) \rceil = \\ h_j\beta \text{ and } \sum_{k=1}^j (\lceil \log(\max_{1 \leq i \leq n} \pi_{j(q-1)+k}(x_i) + 1) \rceil) \leq h_j\beta. \end{array}$

Therefore, it can be inferred that

$$\Delta C \ge (h_i \beta - h_i \beta) n = 0.$$

24 return β' ;

Proposition 3. If the number of run-lengths of j-th sub-column satisfies $l_j \geq \frac{BPE(X,j,\beta)}{\beta + \lceil \log(n+1) \rceil}$, we can infer that

$$RLE(X, j, \beta) \ge BPE(X, j, \beta).$$

Proof. According to $l_j \geq \frac{BPE(X,j,\beta)}{\beta+\lceil\log(n+1)\rceil}$ and Definition II.6, we could infer that

$$RLE(X, j, \beta) = l_j(\beta + \lceil \log(n+1) \rceil)$$

$$\geq BPE(X, j, \beta).$$