

Efficient Structural Clustering on Probabilistic Graphs

Consider an unweighted and undirected probabilistic graph $G = (V, E, P)$ where V is the set of vertices, E is the set of edges, and P denotes the set of probabilities. In G , each edge $e \in E$ is associated with a probability $P_e \in P$

Let $G' = (V, E_G)$ be a possible world which is realized by sampling each edge in G according to the probability P_e clearly we have $E_G \in E$ the probability $Pr[G'|G]$ of sampling this possible world is calculated as

$$Pr[G'|G] = \prod_{e \in E_G} P_e \prod_{e \in E \setminus E_G} (1 - P_e)$$

we make use of $G' \subseteq G$ to indicate that G is a possible world of G' clearly there are a total of $2^{|E|}$ possible worlds in graph G because each edge provides a binary sampling decision. for convenience, we use a notation G to denote a probabilistic graph, and utilize a notation G' to denote a possible world or a deterministic graph.

Definition

1. Structural Neighborhood

Given a deterministic graph $G = (V, E_G)$ the structural neighborhood of a vertex $u \in V$ denoted by $N[u]$ is the closed neighborhood of u

the Structural neighborhood of a vertex includes itself

2. Structural Similarity

Given a deterministic graph $G = (V, E_G)$ the structural similarity between vertices u and v , denoted by $\sigma(u, v)$ is defined as the number of common vertices in $N[u]$ and $N[v]$ normalized by $|N[u] \cup N[v]|$

$$\sigma(u, v) = \frac{|N[u] \cap N[v]|}{|N[u] \cup N[v]|}$$

3. ϵ -Structural Similarity

Given any two neighbor vertices u, v , and a similarity threshold ϵ , u is structural similar to v in a deterministic graph G if $\sigma(u, v) \geq \epsilon$ and $e = (u, v) \in E_G$

Problem Formulation

Definition

1. Probability of Structural Similarity

Given a similarity threshold $0 < \epsilon \leq 1$ the probability of structural similarity that $\sigma(e) \geq \epsilon$ is defined as the sum of the probabilities of all the possible worlds $G' \subseteq G$ such that the structural similarity of $e = (u, v)$ is no less than ϵ in each possible world G

$$Pr[e, \epsilon] = \sum_{G' \subseteq G} Pr[G'|G] \cdot I(\sigma(e) \geq \epsilon)$$

where $I(\sigma(e) \geq \epsilon)$ is a indicator function which equals 1 if $\sigma(e) \geq \epsilon$ and 0 otherwise. If $e \notin E_G$ $I(\sigma(e) \geq \epsilon) = 0$

2. Reliable Structural Similarity

Given an edge $e = (u, v)$ and a threshold η , u is called reliable structural similar to v if $Pr[e, \epsilon] \geq \eta$

3. (ϵ, η) -Reliable Neighborhood

Given a similarity threshold $0 < \epsilon \leq 1$ and a probability threshold $0 < \eta \leq 1$ the (ϵ, η) -reliable neighborhood of u is defined as the subset of vertices in $N[u]$ such that $Pr[e = (u, v), \epsilon] \geq \eta$

A vertex is termed as a reliable core vertex if it has a sufficient number of reliable similar neighbors.

4. (ϵ, η, μ) -Reliable Core Vertex

Given a similarity threshold $0 < \epsilon \leq 1$, a probability threshold $0 < \eta \leq 1$, and an integer $\mu > 2$ a vertex u is a (ϵ, η, μ) -reliable core vertex if $|N_{(\epsilon, \eta)}[u]| \geq \mu$

5. Reliable Structural reachable

Given parameters $0 < \epsilon \leq 1, 0 < \eta \leq 1$ and $\mu \geq 2$ vertex v is a reliable structural reachable from vertex u if there is a sequence of vertices $v_1, v_2, \dots, v_l \in V (l \geq 2)$ such that

- $v_1 = u$ and $v_l = v$
- v_1, v_2, \dots, v_{l-1} are reliable core vertices;
- $v_{i+1} \in N_{\epsilon, \eta}(v_i)$ for $1 \leq i \leq l - 1$

The Probabilistic Graph Clustering Problem Given a probabilistic graph $G = (V, E, P)$ and parameters $0 < \epsilon \leq 1, 0 < \eta \leq 1$ and $\mu \geq 2$ the problem of probabilistic graph clustering is to compute the set \mathbb{C} of reliable clusters in G , Each reliable cluster $C \in \mathbb{C}$ should have at least two vertices and satisfy:

- **Maximality** for each reliable core vertex $u \in C$, all vertices that are reliable structure-reachable from u must belong to C ;
- **Connectivity** for any two vertices $v_1, v_2 \in C$ there existed a vertex $u \in C$ such that both v_1 and v_2 are reliable structure-reachable from u

6. Hub and Outlier

Given the set of \mathbb{C} of reliable clusters in a probabilistic graph G , a vertex u that not in any reliable cluster in \mathbb{C} is a hub vertex if it connects two or more reliable clusters, and it is an outlier vertex otherwise.

for each $e = (u, v) \in G$ the number of possible values of the structural similarity

between u and v over all the possible worlds can be bounded by $O(k_{join} \times k_{union})$, where

$$k_{join} = |\bar{N}[u] \cap \bar{N}[v]| \text{ and } k_{union} = |\bar{N}[u] \cup \bar{N}[v]|$$

记 $N(u) = N[u] \setminus u$ 记 $N(v) = N[v] \setminus v$ 记 $NV[e] = N(u) \cup N(v)$ 将 $NV[e]$ 中的顶点按照顶点ID进行排序。

对于一条边 $e = (u, v)$, $\sigma(e) = \frac{m}{n}$

现在记 $NV'[e] = \{u, v\}$ $X(0, 2, 2) = P_e$,

现在按顺序在 $NV[e]$ 中取第 h 个元素 $w_h = NV[e][h]$, 将其加入到 $NV'[e]$ 中, 对于新加入的顶点, 顶点 u, v 和该顶点分别存在连接 $e_1 = (u, w_h)$ $e_2 = (v, w_h)$

对于下面的三种情况

1. 边 e_1, e_2 同时存在, 则在这一步中, $m_{new} = m_{pre} + 1$ $n_{new} = n_{pre} + 1$ 概率

$$X(h+1, m_{new}, n_{new}) = P_{e_1} P_{e_2} X(h, m_{pre}, n_{pre})$$

2. 边 e_1, e_2 只有一条边存在, 在该步中, $m_{new} = m_{pre}, n_{new} = n_{pre} + 1$

$$X(h+1, m_{new}, n_{new}) = (P_{e_1}(1 - P_{e_2}) + (1 - P_{e_1})P_{e_2})X(h, m_{pre}, n_{pre})$$

3. 边 e_1 和 e_2 都不存在, 在该步中, $m_{new} = m_{pre}, n_{new} = n_{pre}$

$$X(h+1, m_{new}, n_{new}) = (1 - P_{e_1})(1 - P_{e_2})X(h, m_{pre}, n_{pre})$$

综上

$$\begin{aligned} X(h+1, m_{new}, n_{new}) &= P_{e_1} P_{e_2} X(h, m_{pre}, n_{pre}) \\ &\quad + (P_{e_1}(1 - P_{e_2}) + (1 - P_{e_1})P_{e_2})X(h, m_{pre}, n_{pre}) \\ &\quad + (1 - P_{e_1})(1 - P_{e_2})X(h, m_{pre}, n_{pre}) \end{aligned}$$

伪代码如下：

Input: $G=(V,E,P)$, an edge $e = (u, v) \in E$, and similarity threshold ϵ

Output: the probability $Pr(e, \epsilon)$ when the structural similarity of e is no less than ϵ

1. Initialize $X(h, m, n) \leftarrow 0$, for all $h \in [0, k_{union}]$, $m \in [0, k'_{join}]$, and $n \in [0, k'_{union}]$.
2. $Pr(e, \epsilon) \leftarrow 0$
3. $X(0, 2, 2) \leftarrow 1$
4. **for** h in $range(1, k_{union} - 2)$:
5. $e_1 = (u, w_h), e_2 = (v, w_h)$
6. **for** n in $range(2, k'_{union} - 2)$:
7. **for** m in $range(2, \min(n, k'_{join}))$:

$$X(h, m, n) = p_{e_1} p_{e_2} X(h-1, m-1, n-1) \\ + ((1-p_{e_1})p_{e_2} + p_{e_1}(1-p_{e_2}))X(h-1, m, n-1) \\ + (1-p_{e_1})(1-p_{e_2})X(h-1, m, n)$$
8. **for** n in $range(2, k_{union})$:
9. **for** m in $range(\lceil n\epsilon \rceil, \min(n, k_{join}))$:
10. $Pr(e, \epsilon) = Pr(e, \epsilon) + X(k_{union} - 2, m, n)$
11. **return** $P_e * Pr(e, \epsilon)$

时间复杂度分析

对于一条边 e 计算 $P(e, \epsilon)$ 的时间复杂度是 $O(k_{union}^2 k_{join})$ $k_{union} \leq 2 * d_{max}$

$k_{join} \leq \min\{d_u, d_v\}$, 原式的上界为 $O(d_{max}^2 \times \sum_{(u,v) \in E} \min\{d_u, d_v\}) = O(d_{max}^2 \times \alpha \times m)$

α denotes the arboricity of the graph G and $m = |E|$

空间复杂度

在计算时，需要使用一个二维矩阵存储值，空间复杂度为 $O(k_{union} k_{join})$

Optimization

1. Basic Pruning Rules

◦ Pruning Improper Edges

For any edge $e = (u, v) \in E$ if $P_e < \eta$ we have $Pr[e, \epsilon] < \eta$

◦ Avoiding Duplicate Computation

For any edge $e = (u, v) \in E$, $Pr[e = (u, v), \epsilon] = Pr[e = (v, u), \epsilon]$ always holds

2. Early Termination

在第 h 次的计算中，如果 $N[u] \cap N[v]$ 中的所有节点都被处理，如果此时小于 ϵ 则在处理非公共节点的时候，不会再大于 ϵ

Algorithm 3. Improved DP for Computing $\Pr(e, \epsilon)$

```

1  if  $p_e < \eta$  then
2    return; /* Property 1 pruning rule */
3  Lines 1-3 in Algorithm 2;
4  for  $h \leftarrow 1$  to  $k_{union} - 2$  do
5    for  $m' \leftarrow 2$  to  $\min\{h + 2, k_{join}\}$  do
6       $\tau \leftarrow \frac{m'}{\epsilon}$ ;
7      for  $n' \leftarrow m'$  to  $\min\{h + 2, k_{union}\}$  do
8        if  $h > k_{join} - 2$  and  $n' \geq \tau$  then
9          break; /* early termination */
10      $X(h, m', n') \leftarrow p_{(w_h, u)} p_{(w_h, v)} X(h - 1, m' - 1, n' - 1) +$ 
         $((1 - p_{(w_h, u)}) p_{(w_h, v)} + p_{(w_h, u)} (1 - p_{(w_h, v)})) X(h - 1, m',$ 
         $n' - 1) + ((1 - p_{(w_h, u)}) (1 - p_{(w_h, v)})) X(h - 1, m', n')$ 
11  Lines 8-11 in Algorithm 2;

```

3. Pruning by Lower and Upper Bounds

对于分母来说, $n \leq k_{union}$ 如果固定分母为 k_{union} 我们能够得到 $\Pr[e, \epsilon]$ 的下界。

则在变量 $X(h, m, n)$ 中, n 不起作用, 源公式可简化为

$$X(h, m) = P_{e_1} P_{e_2} X(h - 1, m - 1) + (((1 - P_{e_1}) P_{e_2} + P_{e_1} (1 - P_{e_2})) + (1 - P_{e_1})(1 - P_{e_2})) X(h - 1, m)$$

对于分子来说, $m \leq k_{join}$ 固定分子为 k_{join} , 可以得到 $\Pr[e, \epsilon]$ 的上界

在变量 $X(h, m, n)$ 的计算中, m 不起作用, 原公式可以简化为

$$X(h, n) = (P_{e_1} P_{e_2} + P_{e_1} (1 - P_{e_2}) + P_{e_2} (1 - P_{e_1})) X(h - 1, n - 1) + (1 - P_{e_1})(1 - P_{e_2}) X(h - 1, n)$$

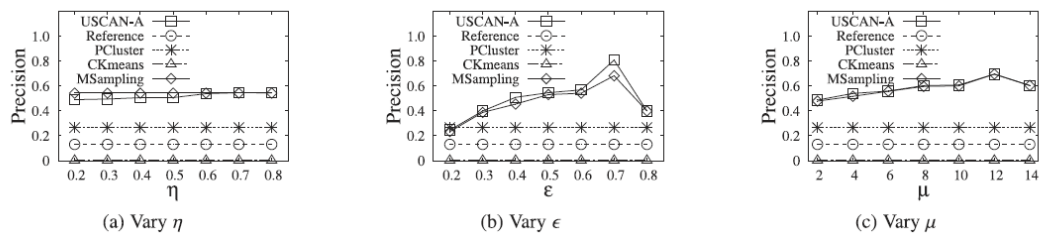
一个约束更强的上界

将 $V = (N[u] \cup N[v]) \setminus (N[u] \cap N[v])$ 中的节点去除, 不参与 $\Pr[e, \epsilon]$ 的计算。

因为将 V 中的节点加入到集合中, 会增加分母, 减小数值。

实验结果

1. Clustering Precision with Varying Parameters



2. Average Expected Density of Different Algorithms.

$$AED = \frac{1}{n'} \times \sum_{i=1}^{n'} \sum_{e_j \in E_i} p(e_j) \times / (|V_i| \times (|V_i| - 1))$$

n' 是聚类的个数

E_i 是第 i 个类的边的个数

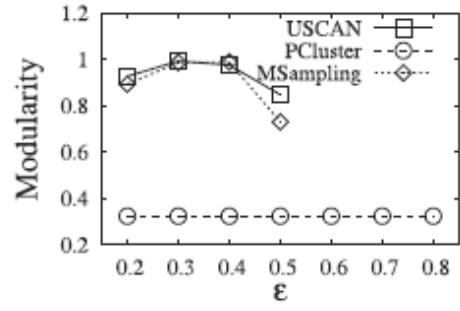
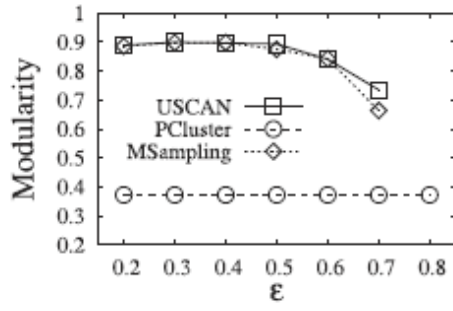
V_i 是第 i 个类的点的个数

3. Expected Modularity of Various Algorithms

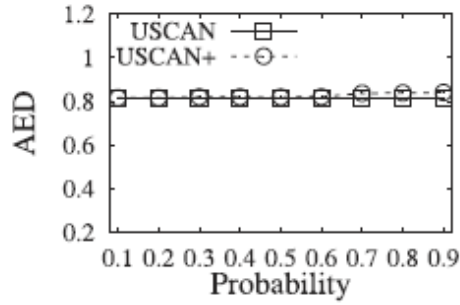
$$\bar{Q} = \frac{1}{N} \times \sum_{G' \in G} Q_{G'}$$

G' 是概率图 G 的一种可能, N 是 G 中可能的个数

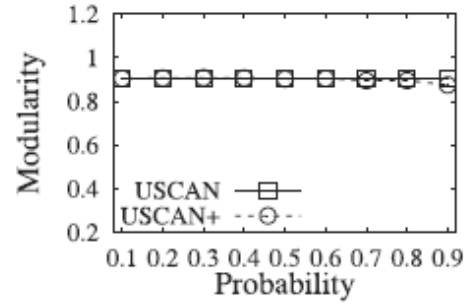
$Q_{G'}$ 是 modularity of G'



4. Sensitive Analysis

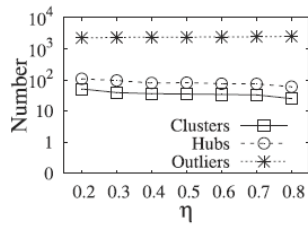


(a) AED

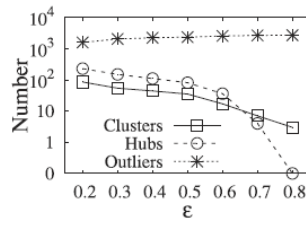


(b) Modularity

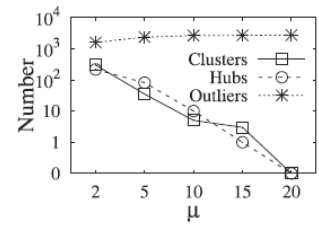
5. Statistics of the Reliable Structural Clustering.



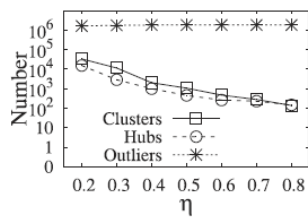
(a) Vary η (CORE)



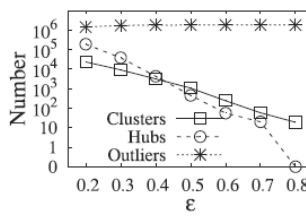
(b) Vary ϵ (CORE)



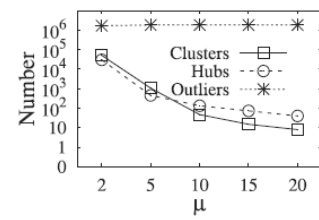
(c) Vary μ (CORE)



(d) Vary η (DBLPAll)

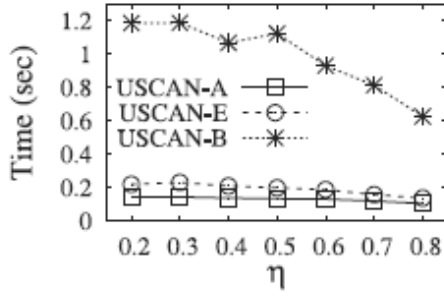


(e) Vary ϵ (DBLPAll)

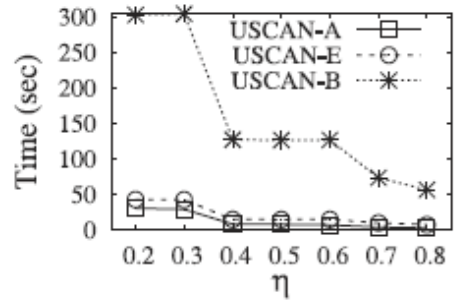


(f) Vary μ (DBLPAll)

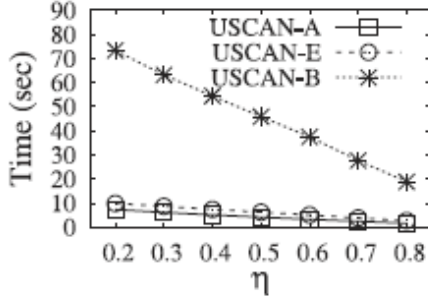
运行时间



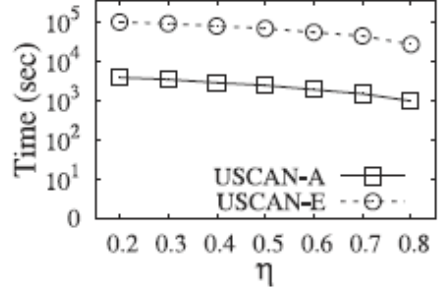
(a) CORE



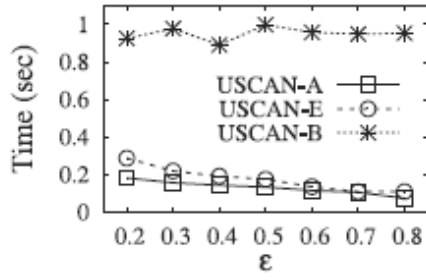
(b) DBLP01



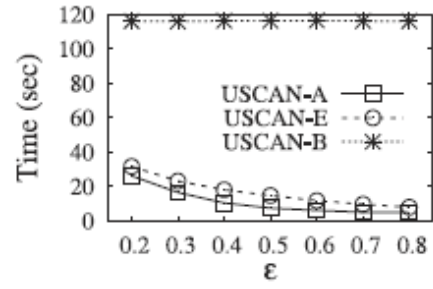
(c) Amazon



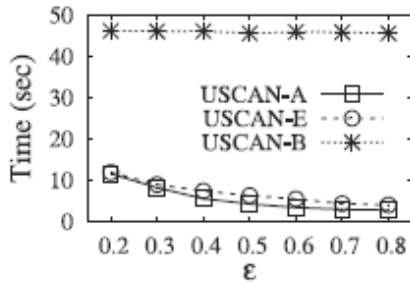
(d) Youtube



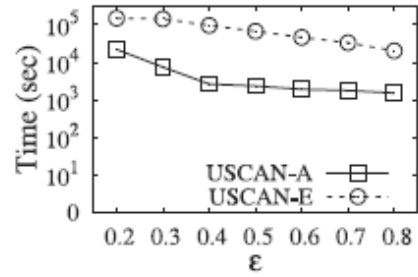
(a) CORE



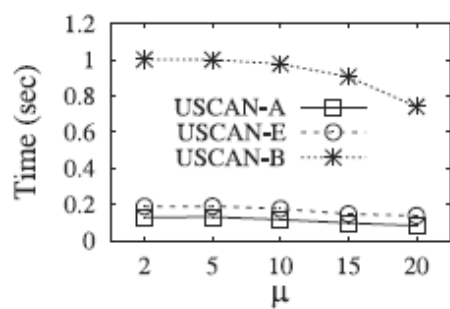
(b) DBLP01



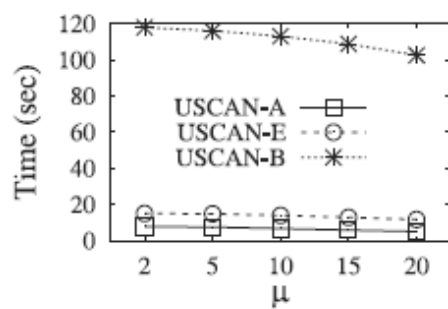
(c) Amazon



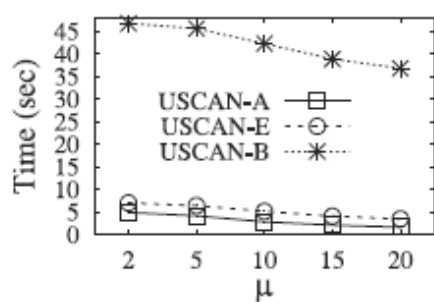
(d) Youtube



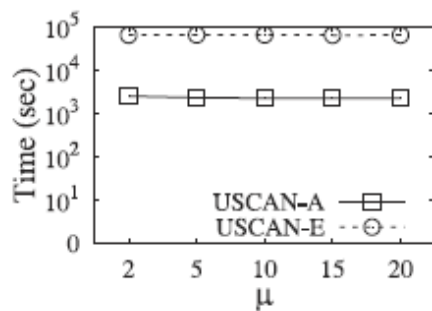
(a) CORE



(b) DBLP01

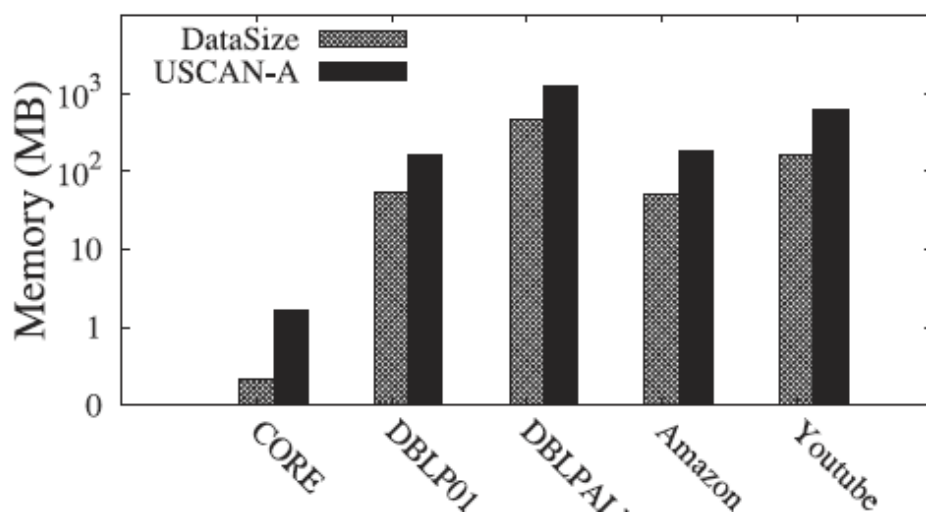


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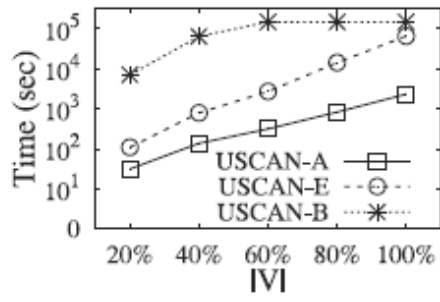


(d) Youtube

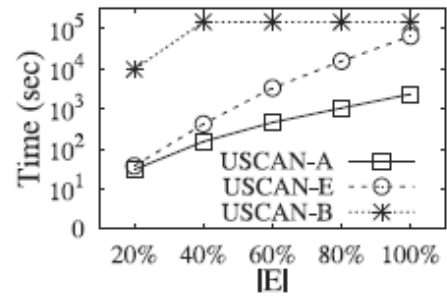
内存消耗



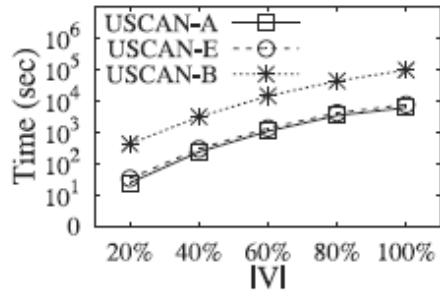
可扩展性



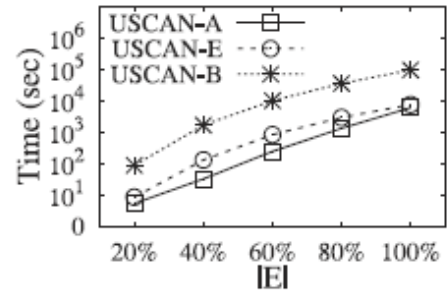
(a) Youtube (vary $|V|$)



(b) Youtube (vary $|E|$)



(c) DBLPAll (vary $|V|$)



(d) DBLPAll (vary $|E|$)