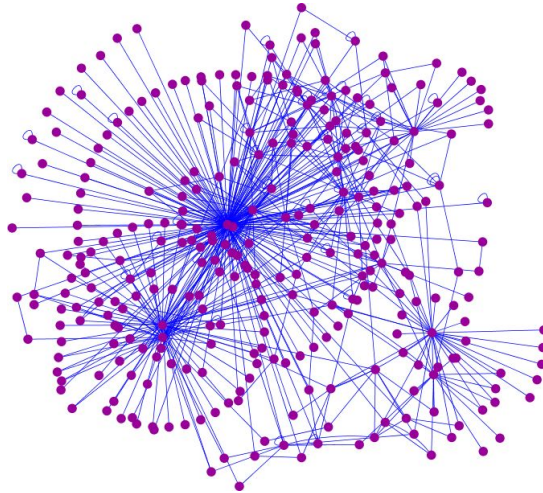


Top-k Similar Graph Matching in Biological Networks



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Introduction

- Biological networks are one of most complex systems
- Relationships between molecules, entities, structural properties
- Crucial to understand life
- Graph based data structures efficient in capturing dynamics of networks
- A variety of static, dynamic graph based methods have been applied

Problem Statement

- Graph matching important to retrieve information embedded in graphs
- Efficient alternative to exact graph matching - approximate graph matching
- Tram algorithm for large graph networks
- Given a graph database and multiple query graphs, find similar substructures from the data graph that match the query graph
- Applications include querying in protein networks - searching, comparing

TraM Algorithm

- Computes similarity between two labelled graphs
- Algorithm computes the topmost k similar graphs based on different similarity criteria. This algorithm's strength lies in the fact that multiple domain dependent similarity scores can be incorporated into an overall similarity calculation of nodes
- Conceptual likeness of two sets of nodes is captured using a domain-dependent similarity function called the σ -similarity function
- Random walk captures structural information of the graph and similarity function is called the β -similarity function

TraM Algorithm

- Before we get into the main algorithm, we need to get familiar with some definitions and helping algorithms

Algorithm 1: Random Walk

Input: Graph $G = (V_g, E_g)$ and Restart Probability β .

Output: Random Walk Score $P_s(V_g)$.

- 1 Let $r_s(V_g)$ be the restart vector with all entries having value $\frac{1}{|V_g|}$;
 - 2 Let A be the column normalized adjacency matrix defined by E ;
 - 3 Initialize $P_s(V_g) = r_s(V_g)$;
 - 4 **while** $P_s(V_g)$ *has not converged* **do**
 - 5 $P_s(V_g) = (1 - \beta) * A * P_s(V_g) + \beta * r_s(V_g)$;
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TraM Algorithm

Definition 2 (β -signature). Let $G = (V_g, E_g)$ be a graph and \mathbb{B} be a set of β values. Random walk score of a node is a function of the form $\omega : V_g \times \mathbb{B} \rightarrow [0, 1]$. An n -dimensional vector $(\omega(v, \beta_1), \omega(v, \beta_2), \dots, \omega(v, \beta_n))$ is called a β -signature of node $v \in V_g$, denoted $\vec{\beta}(v)$ and the set $\beta(G) = \bigcup_{v \in V} \vec{\beta}(v)$ is called the β -signature of G .

Definition 4 (β -similarity). Let $G_1 = (V_{g_1}, E_{g_1})$ and $G_2 = (V_{g_2}, E_{g_2})$ be two graphs and $\beta(G_1)$ and $\beta(G_2)$ be their β -signatures. For any $v_1 \in V_{g_1}$ and $v_2 \in V_{g_2}$, their structural or β -similarity, denoted $\hat{\beta}(v_1, v_2)$, is defined by

$$\hat{\beta}(v_1, v_2) = 1 - \sqrt{\sum_{i=1}^k (a_i - b_i)^2},$$

where $\vec{\beta}(v_1) = (a_1, a_2, \dots, a_k) \in \beta(G_1)$ and $\vec{\beta}(v_2) = (b_1, b_2, \dots, b_k) \in \beta(G_2)$.

TraM Algorithm

Definition 5 (Graph similarity). Let $G_1 = (V_{g_1}, E_{g_1})$ and $G_2 = (V_{g_2}, E_{g_2})$ be two graphs and ϕ be a mapping function. Then, the similarity γ between two graphs G_1 and G_2 under a mapping function ϕ is

$$\gamma(G_1, G_2) = \sum_{\forall v_1, v_2 (v_1 \in V_{g_1}, \phi(v_2) \in V_{g_2})} \sigma(v_1, \phi(v_2)) \times \hat{\beta}(v_1, \phi(v_2)). \quad (2)$$

TraM Algorithm

Definition 6 (δ -neighborhood of nodes). Let Q be a query graph, and r be its radius.¹ Let $D = (V_d, E_d)$ be any graph, and $v \xrightarrow{j} u$ represent j -hop reachability from node v to u . Then, δ -neighborhood of v is the set $\{u | v, u \in V_d \wedge v \xrightarrow{j} u \wedge j \leq r\}$ (including zero hop reachability, i.e., v itself), denoted $\delta(r, v)$.

Definition 7 (Induced subgraphs). Let $G = (V_g, E_g)$ be any graph, and $N \subseteq V_g$ be an arbitrary set of nodes. Then, $G' = (N, E')$ is called an induced subgraph, denoted $\chi(N) = G' = (N, E')$, such that whenever $v, v' \in N$ and $e = (v, v') \in E_g$, e is also in E' , and nothing else is in E' , i.e., G' is a subgraph of G , denoted $G' \sqsubseteq G$.

TraM Algorithm

Algorithm 2: GraphMatch

Input: Data graph $D = (V_d, E_d)$ and query graph $Q = (V_q, E_q)$. Thresholds k , μ_v , μ_s and λ .

Output: Top- k matches of Q .

- 1 Initialize priority queue PQ as empty;
 - 2 Calculate β -signature $\beta(Q)$ for Q ;
 - 3 Compute radius r of Q ;
 - 4 **for** $\forall v_d (v_d \in V_d)$ **do**
 - 5 Compute $\delta(r, v_d)$;
 - 6 **if** $|Filter(\delta(r, v_d), Q, \mu_v, \mu_s)| > |V_q|$ **then**
 - 7 Top- k Match(Q , $\beta(Q)$, D , $\beta(\chi(\delta(r, v_d)))$, λ ,
 PQ);
 - 8 **return** All top k graphs $g \in PQ$;
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TraM Algorithm

Algorithm 4: Filter

Input: Set of nodes $\delta(r, v_d)$ and Graph $Q = (V_q, E_q)$.
Thresholds μ_v and μ_s .

Output: Pruned $\delta(r, v_d)$.

```
1 if  $|\delta(r, v_d)| > |V_q|$  then
2   for every  $v_n \in \delta(r, v_d)$  do
3     Compute candidate subgraph as  $\chi(\delta(r, v_d))$ ;
4     Compute  $\beta$ -signature  $\beta(\chi(\delta(r, v_d)))$  for
        $\chi(\delta(r, v_d))$ ;
5     if  $\forall v_q (v_q \in V_q (\max\{\sigma(v_n, v_q)\} < \mu_v \text{ or}$ 
6        $\max\{\hat{\beta}(v_n, v_q)\} < \mu_s))$  then
7        $\lfloor$  remove  $v_N$  from  $\delta(r, v_d)$ ;
8 return  $\delta(r, v_d)$ ;
```

TraM Algorithm

Algorithm 3: Top- k Match

Input: Query graph $Q = (V_q, E_q)$, $\beta(Q)$, candidate graph $C = (V_c, E_c)$, $\beta(C)$, threshold λ . Queue PQ

Output: Updated priority queue PQ .

```

1 for  $i = 1$  to Number of Nodes in time-stamp 1 do
2    $\lfloor$  initialize  $S^{(i,1)} = \emptyset$  and  $\text{sim}(i, S^{(i,1)})^{(1)} = 0$ ;
3 for  $t = 2$  to  $2 \times |V_q|$  do
4   for  $r = 1$  to Number of Nodes in time-stamp  $t$  do
5     if  $t$  is Even then
6       for  $p = 1$  to Number of Nodes in
7         time-stamp  $t - 1$  do
8         if  $(r \notin S^{(p,t-1)})$  and  $((\exists i(i \in S^{(p,t-1)}$ 
9           and  $r \xrightarrow{1} i$  and  $i \in V_c)))$  and
10           $(\text{sim}(p, S^{(p,t-1)})^{(t-1)} + \sigma(p, r) \times$ 
11             $\hat{\beta}(p, r) \geq \text{MAX})$  then
12             $\text{MAX} = \text{sim}(p, S^{(p,t-1)})^{(t-1)} +$ 
13               $\sigma(p, r) \times \hat{\beta}(p, r);$ 
14             $k = p;$ 
15             $\text{newMAX} = \text{true};$ 
16       if  $\text{newMAX} = \text{true}$  then
17          $S^{(r,t)} = S^{(k,t-1)} \cup \{r\};$ 
18          $\text{sim}(r, S^{(r,t)})^{(t)} = \text{MAX};$ 
19       if  $t$  is Odd or  $\text{newMAX} = \text{false}$  then
20          $S^{(r,t)} = S^{(r,t-1)};$ 
21          $\text{sim}(r, S^{(r,t)})^{(t)} = \text{sim}(r, S^{(r,t-1)})^{(t-1)};$ 
22       if  $t = 2 \times |V_q|$  and last  $r$  then
23          $\gamma(Q, C) = \text{sim}(r, S^{(r,t)})^{(t)};$ 
24 if  $\gamma(Q, C) \geq \lambda$  then
25    $\lfloor$  Add  $\langle C, \gamma(Q, C) \rangle$  to queue  $PQ$ ;
26 return  $PQ$ 

```
