Preserving Privacy in Social Networks Against Neighborhood Attacks

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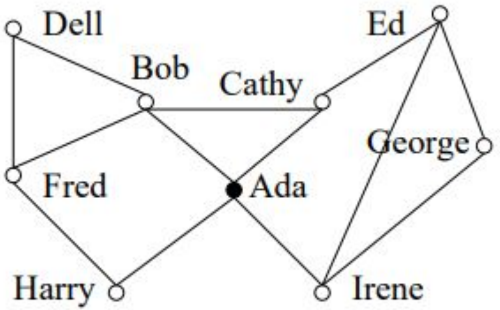
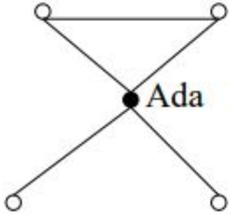
Neighborhood Attack

- Removing node and edge labels does not protect privacy.
- Having information about neighbors of a target victim and the relationship among the neighbors, it is possible to re-identify the target victim in an anonymized network.
- Using neighborhood attack, it is possible to analyze the connectivity of the target node and its relative position in the network.

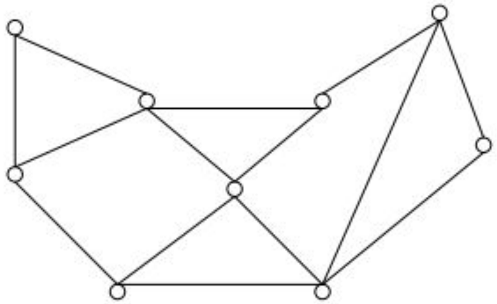


(a) the social network



(c) the 1−neighborhood graph of Ada

Privacy can be provided by using the k – anonymity mode



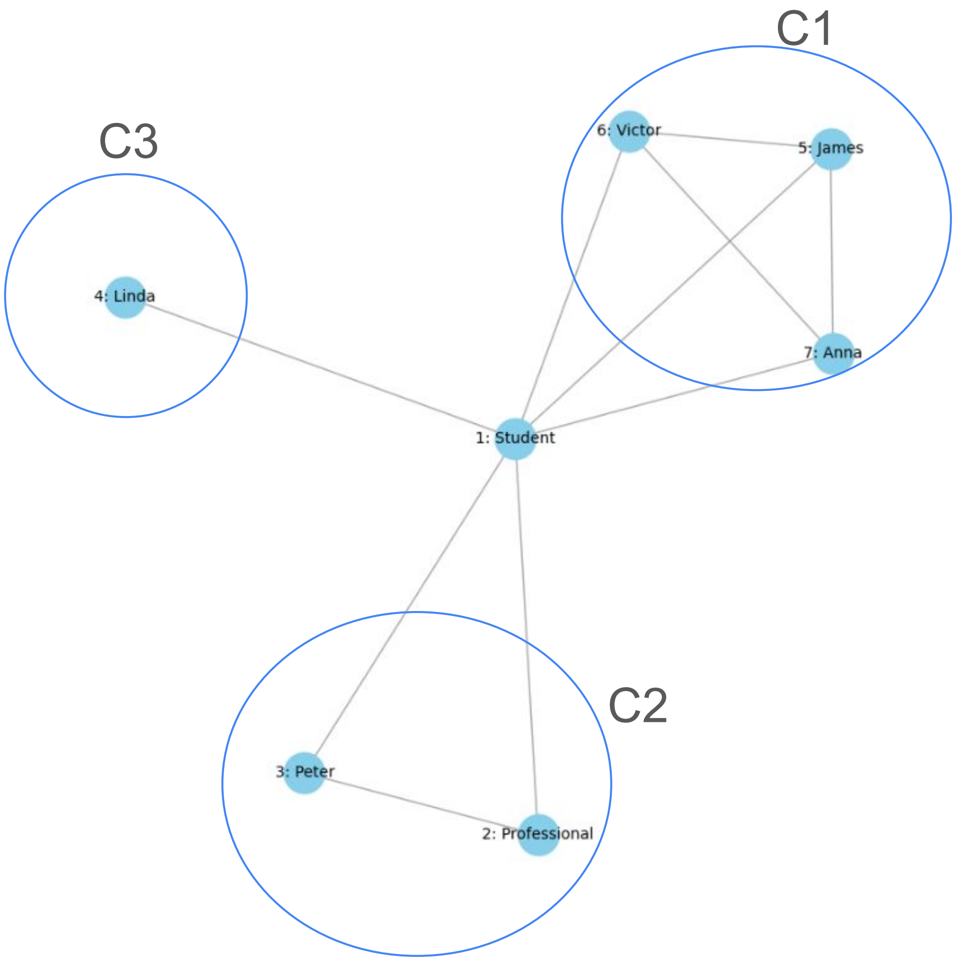
(d) privacy−preserved anonymous network

Neighborhoods extraction

For each vertex *u* in the social network *G*, extract its neighborhood, denoted by *NeighborG(u)*, which is the induced subgraph of *u*'s neighbors.

Workflow:

- **Neighborhood Component Decomposition:** Divide each neighborhood *NeighborG(u)* into its maximal connected subgraphs, called neighborhood components. (*C1, C2, and C3.*)
- **DFS Code Generation:** For each neighborhood component *C*, generate its best Depth-First Search (DFS) code to solve the uniqueness problem.
- **Neighborhood Component Code Construction:** Combine the minimum DFS codes of all components in a neighborhood to create the neighborhood component code (NCC) for the vertex *u*.



DFS representation

Goal: find a best representation to ensure matching during a component anonymization.

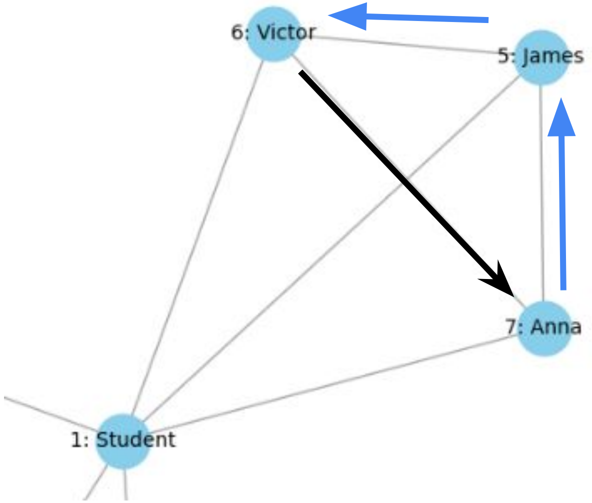
For each neighborhood component *C*, generate its Depth-First Search (DFS) code as follows:

- Choose a starting vertex and perform a depth-first traversal of the component *C*.
- Represent each edge as (*vi, vj, L(vi), L(vj)*), where *vi* and *vj* are the vertices of the edge, and *L(vi)* and *L(vj)* are their corresponding labels.
  List all edges in the order ≺, which prioritizes **forward edges** (edges in the DFS tree) over **backward edges**, and within each category, sorts based on vertex indices.

$F: \{(v_0, v_1), (v_1, v_2)\}$

$B: \{(v_2, v_0)\}$

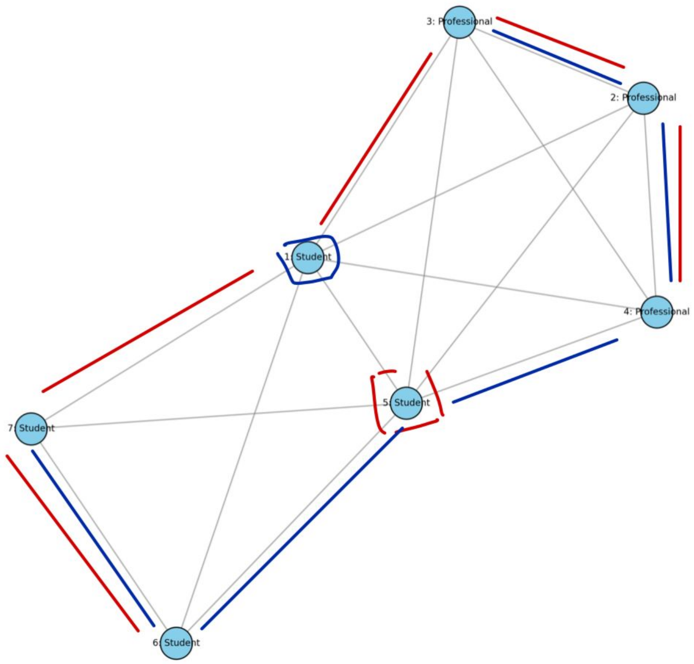
$R: \{(v_0, v_1), (v_1, v_2), (v_2, v_0)\}$




```
(0, 1, 'Anna', 'James')
(1, 2, 'James', 'Victor')
(2, 0, 'Victor', 'Anna')
```

Neighborhoods Anonymization

K=2 for G=(1,5)



The overall goal is to make any individual vertex indistinguishable from at least *k*-1 others in the anonymized network, thereby limiting the confidence of an adversary performing a neighborhood attack.

Workflow:

Anonymization Cost: A cost function is defined to measure the information loss incurred during anonymization. This cost considers label generalization (using a normalized certainty penalty) and edge additions.
Greedy Anonymization: The algorithm processes vertices in descending order of neighborhood size, aiming to minimize information loss for high-degree vertices.
Vertex Grouping: For each "seed" vertex, *k*-1 other vertices with the most similar neighborhoods (lowest anonymization cost) are identified and grouped together.
Neighborhood Isomorphism: The neighborhoods within each group are made isomorphic.

Anonymization Cost

A cost function measures the similarity between the neighborhoods of two nodes in a social network. The smaller the cost function, the more similar the two neighborhoods are.

The cost function is calculated using the following parameters:

- **α**: This weight is applied to the normalized certainty penalty (NCP), which quantifies the information loss resulting from generalizing the labels of vertices.
- **β**: This weight is associated with the information loss due to adding edges to the social network.
- **γ**: This weight is assigned to the number of vertices linked to the anonymized neighborhoods to achieve k-anonymity

```
while VertexListCopy:
    # Select seed vertex
    SeedVertex = VertexListCopy.pop(0)

    # Calculate costs for all remaining vertices
    costs = [(anon.cost(anon.G_prime.neighborhoods[SeedVertex], anon.G_prime.neighborhoods[v], alpha, beta, gamma), v) for v in VertexListCopy]
    costs.sort(key=lambda x: x[0])  # Sort by cost

    # Create candidate set
    if len(VertexListCopy) >= 2 * k - 1:
        CandidateSet = [v for _, v in costs[:k - 1]]
    else:
        CandidateSet = VertexListCopy

    # Anonymize the neighborhoods
```

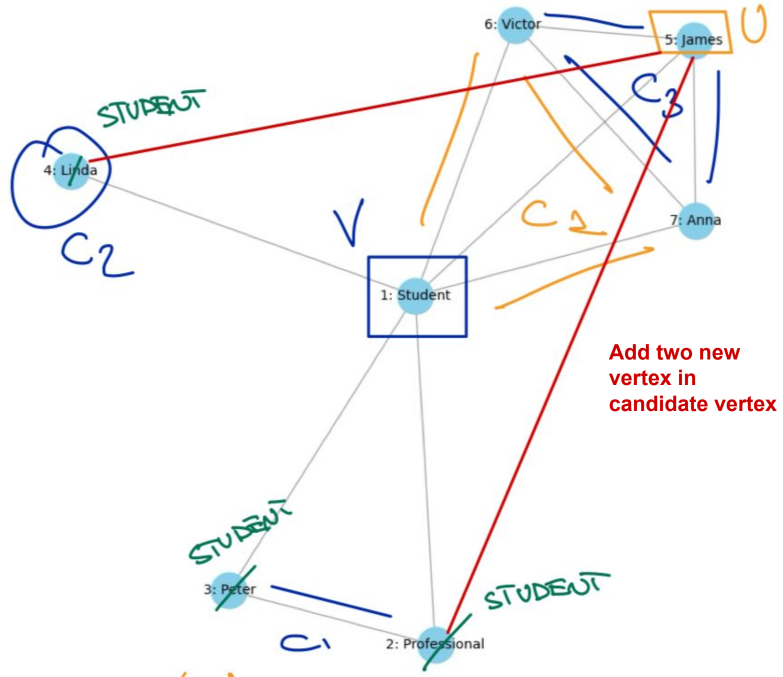
Neighborhoods Isomorphism

#comp_v = 2 > #comp_u = 0

Two components perfectly match each other if they have the same minimum DFS code

Steps

- **Add vertex to component**: Ensure both components have the same number of vertices by repeatedly adding vertices to the smaller component.
- **Label Generalization:** For any pair of matched vertices that have different labels, apply a label generalization technique to assign a common generalized label to both nodes.
- **Edge Alignment**:Compare the two adjacency matrices (A for comp_v and B for comp_u) and add missing edges to either component where one has an edge and the other does not, ensuring both matrices become identical.



$$\begin{array}{cc} & \begin{array}{cc} 3 & 2 \end{array} \\ \begin{array}{c} 3 \\ 2 \end{array} & \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \end{array} \;\Big|\; \begin{array}{cc} & \begin{array}{cc} 4 & 2 \end{array} \\ \begin{array}{c} 4 \\ 2 \end{array} & \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \end{array} \longrightarrow \begin{array}{cc} & \begin{array}{cc} 4 & 2 \end{array} \\ \begin{array}{c} 4 \\ 2 \end{array} & \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \end{array}$$

Vertex addition

A vertices are added during component balancing and select a best candidate:

```
while len(comp_v) < len(comp_u):
    addVertexToComponent(comp_v, seed_vertex)
while len(comp_u) < len(comp_v):
    addVertexToComponent(comp_u, candidate_vertex)
```

Label Generalization

```
def get_generalization_level(self, label):
    """Return the generalization level for a given label.
    If label is missing, return 0 (lowest)."""
    if label is None:
        return 0
    return self.label_hierarchy.get(label, 0)
```

```
def addVertexToComponent(component, owning_vertex):
    if component:
        candidates = [node for node in self.G_prime.N
                            if not node.Anonymized
                            and node.node_id != owning_vertex.node_id
                            and node.node_id not in [node.node_id for node in component]]
    else:
        candidates = [node for node in self.G_prime.N
                            if not node.Anonymized
                            and node.node_id != owning_vertex.node_id
                            and node.node_id not in owning_vertex.edges]
    if candidates:
        selected = min(candidates, key=lambda n: len(n.edges))
    else:
        if component:
            candidates = [node for node in self.G_prime.N
                                if node.node_id != owning_vertex.node_id
                                and node.node_id not in [node.node_id for node in component]]
        else:
            candidates = [node for node in self.G_prime.N
                                if node.node_id != owning_vertex.node_id
                                and node.node_id not in owning_vertex.edges]
        if candidates:
            selected = min(candidates, key=lambda n: len(n.edges))
            self.check_and_remove_anonymized_group(selected)
        else:
            raise ValueError("No more candidates available for anonymization.")
    component.append(selected)
    selected.addEdge(owning_vertex.node_id)
    owning_vertex.addEdge(selected.node_id)
    affected_nodes.add(selected)
    affected_nodes.add(owning_vertex)
```

Empirical Evaluation

- **Computational Complexity:** The algorithm has exponential complexity, making it infeasible to test on large datasets.
- **Experimental Constraints:** Due to time and computational limitations, we conducted experiments on very small datasets.
- **Synthetic Data Generation:** A fake data generator was created to generate datasets of any size, allowing controlled testing.
- **Limitations of Small Datasets:** The algorithm is designed for larger graphs, so testing on small datasets (30 nodes) does not reflect real-world performance. Results may not be reliable or indicative of actual scalability and effectiveness.
- **Experimental Outcome:** Presented anonymization results on a 30-node dataset, highlighting performance issues due to limited data.

```
Final Anonymization Metrics:
  Edges added: 379
  Labels anonymized: 23
  Runtime: 77.7743 seconds

=== Testing Different Parameter Combinations ===

Testing with parameters: α=3, β=1, γ=1
  Edges added: 382
  Labels anonymized: 23
  Runtime: 100.5071 seconds

Testing with parameters: α=1, β=3, γ=1
  Edges added: 382
  Labels anonymized: 23
  Runtime: 104.3571 seconds

Testing with parameters: α=1, β=1, γ=3
  Edges added: 379
  Labels anonymized: 23
  Runtime: 79.9467 seconds

=== Calculating Utility Loss ===

Utility Loss Analysis:
  Average Label Loss: 0.66 (0 = no distortion, 1 = maximum distortion)
  Edge Loss (Proportion of Added Edges): 7.150943
```