Privacy and Anonymity in Graph Data

Michael Hay, Siddharth Srivastava, Philipp Weis

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Outline

1. Introduction
2. Emipirical Analysis of Data Disclosure
3. Modelling Privacy and Disclosure for Graph Data
4. Graph Anonymization Techniques

Single-table anonymization

What anonymization is about:

- Want to publish data about invidivuals without revealing any private information
- Examples: census data, medical records, network traces, ...
- High level idea: separate sensitive from non-sensitive information, and remove all (or most) sensitive information

Anonymization of single-table data is studied widely and used in practice.

k-Anonymity

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[FL, GU]	[96932, 99401]	PAXSON COMMUNICATIONS CORP	REP	2000
[FL, GU]	[96932, 99401]	PAXSON COMMUNICATIONS CORP	DEM	300
[FL, GU]	[96932, 99401]	PAXSON COMMUNICATIONS CORP	DEM	300
[FL, GU]	[96932, 99401]	PAXSON COMMUNICATIONS CORP	DEM	1000
[FL, GU]	[96932, 99401]	PAXSON COMMUNICATIONS CORP	REP	300
[FL, GU]	[96932, 99401]	PAXSON COMMUNICATIONS CORP	DEM	500
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MA	01002	[AMHERST COLLEGE, BULKELY RICHARDSON]	DEM	250
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Goals of the Project

- Obtain examples of graph data, get a feeling for private and non-sensitive properties of these graphs, experiment with re-identification
- Develop a theoretical framework for graph data publication, privacy, anonymization and information disclosure
- Investigate conventional anonymization techniques on graph data. Where do they fail?
- Develop new techniques that can be used to anonymize graph data

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Adversary's Perspective on Graph Anonymization

- What properties about the real-world can the adversary infer from published data?
- We investigate the following **re-identification** task:
  input:
  - a set of real-world objects (Enron employees)
  - some background knowledge about the objects
  - a published graph (email communications), 'anonymized' by removing object identifiers (e.g. *joe@enron.com* becomes v_{10})

  output:
  - map each real-world object to a vertex (or a subset of vertices) in the published graph (e.g. *joe@enron.com* $\rightarrow \{v_4, v_{10}, v_{17}, v_{65}\}$)
- Turns out re-identification can be succinctly described as a constraint satisfaction problem (CSP), except enumerate all assignments rather than find a single assignment

What is a Constraint Satisfaction Problem?

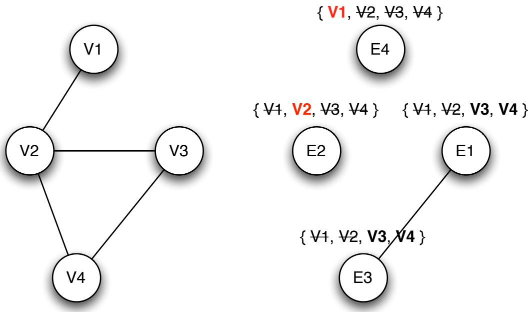
- A CSP is defined by:
  - a set of **variables** $X_1, \ldots, X_n$
  - each variable X_i has a **domain** D_i of possible **values**
  - a set of **constraints** $C_1, \ldots, C_m$ which constrain the possible values that a variables can take on
  - A **solution** is an assignment of variables to values such that constraints are satisfied.
  - Any CSP can be represented as a **constraint graph**: one vertex per variable and an edge for each binary constraint.

Re-identification as a CSP

- **variables**: one per real-world object
- **domains**: the set of vertices in published graph $\{v_1, \ldots, v_n\}$
- **constraints**: background knowledge
  - unary constraints: $degree(o_i)$, $connected\_component\_size(o_i)$
  - binary constraint: $edge(o_i, o_j)$, $path_k(o_i, o_j)$
  - n-ary constraint: $all\_different(o_1, \ldots, o_n)$
- **solution**: for each object o, the set of plausible vertices. I.e. a subset of vertices $V' \subseteq \{v_1, \ldots, v_n\}$ such that when o was mapped to $v \in V'$ a valid solution was found
- **constraint graph**: surprisingly sparse, so CSP solver runs fast!

Toy Example

PUBLISHED GRAPH CONSTRAINT GRAPH



Background Knowledge:
degree(E2) = 3
edge(E1,E3)

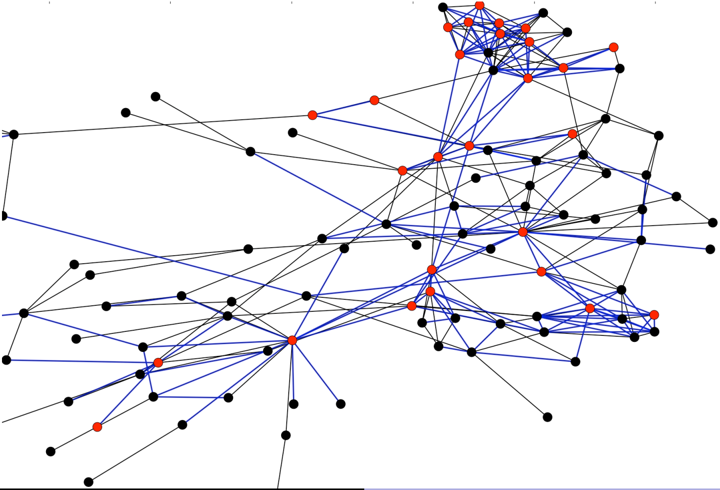
Empirical Analysis: How does background knowledge help?

Email communications of 117 Enron employees, private data that is now part of public record (following subpoena). Task: re-identify Enron employees in graph of email communication (edge means ≥ 5 emails both directions).

Background Knowledge	Ave. Domain Size	No. Reidentified
None	117	0 (out of 117)
Centrality Quartile	29.2	0
Degree Only	13.2	4
Degree And Centrality Quartile	5.4	12
25% edges	-	-
Degree And 25% edges	8.2	28
Degree And 50% edges	2.40	63

Re-identifying Enron Employees from Emails

Background knowledge was node degree and a sample of 25% of the edges (shown in blue), weighted by frequency of communication. Red nodes have been re-identified.



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Node properties and types

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Classify nodes in the graph with respect to their properties. The type of a node is a summary of all relevant properties of a node. Types contain information like

- Node attributes (just as in the tabular case)
- Degree
- Centrality
- Neighborhood information

Anonymization with node types

How we anonymize our data

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Background knowledge $\kappa : N \to \mathcal{P}(V)$ or $\kappa : N \to \mathcal{P}(T)$.
Compare this to knowledge after the publication κ'.

Background Knowledge and Disclosure

Background knowledge $\kappa : N \rightarrow \mathcal{P}(V)$ or $\kappa : N \rightarrow \mathcal{P}(T)$ (or probability distributions).

To guarantee k-anonymity: for all individuals $n \in N$: $\kappa'(n) \geq k$. Ignore adversary's background knowledge here.

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Consider different distance measures $d(\kappa, \kappa')$ to measure the amound of disclosure.

$$d_{\max}(\kappa, \kappa') = \max \left\{ \frac{\kappa(n) - \kappa'(n)}{\kappa(n)} \,\middle|\, n \in N \right\}$$

Include distance measure between types.

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Hurdles in Guaranteeing Privacy in Graphs

From	To	Count
Samson	Delilah	50
Arthur	Merlin	65
Alice	Bob	0
Delilah	Alice	50

Anonymizing Graphs is Difficult

- Tuples are interdependent: cannot merge tuples on any single attribute without possibly disturbing the others or making the graph inconsistent. Renders most anonymization algorithms infeasible.
- Each individual could occur in several tuples but still need not by anonymized.

Degree-Types: A Simple Case

Node-Degree is a simple yet interesting node type to consider.

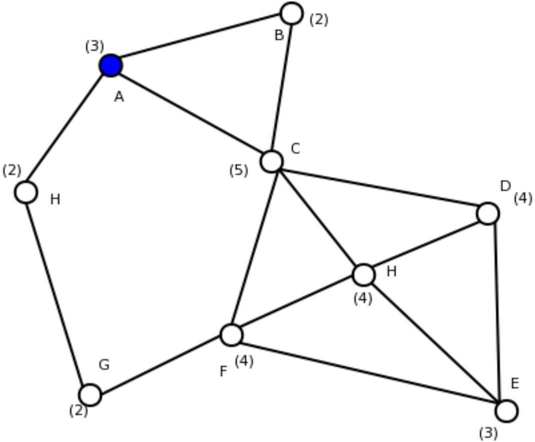
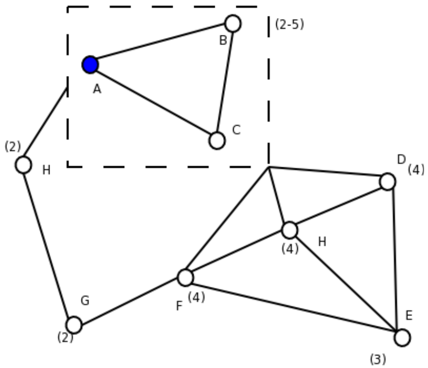


Figure: A Component of Enron Email Communication Graph (only senior/known employees)

Providing Privacy for Degree-Types

- We wish to anonymize without creating false information. Adding/deleting edges to manipulate degrees is ruled out.
- Can add vagueness to the graph.
- Only way to manipulate degrees is to generalize nodes or edges.
- Generalizing nodes is easier. Edge generalization causes more side effects.

A Connectivity Respecting 3-Anonymization on Degree



We can keep the edges of triangle A, B, C because there is one edge between every pair.

How did we do that?

- Basic Idea: merge nodes until all degree-types have at least k nodes.
- Any such grouping will work - but some groupings are better at preserving graph properties than others.

Naive Degree-Based Anonymization

While (! k-anonymized)

1. Find lowest degree with fewer than k nodes.
2. Merge its nodes with nodes of next largest degree with fewer than k nodes.

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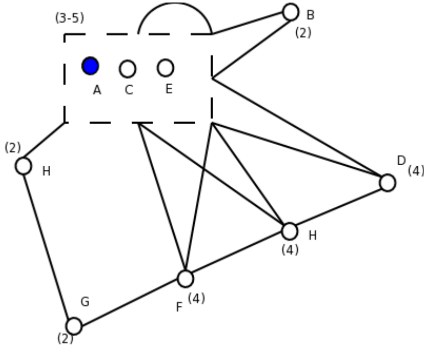
Comparison of The Two Approaches

- Problem: Does not care about graph structure!
- However, it keeps the Type-ranges small.
- Two counter-acting aspects of utility: Graph Structure and Type-Range.

Result of Naive Degree-Based Anonymization



Advantage: smaller degree ranges.

Degree-Types and k-anonymization

It turns out that achieving privacy for Degree-Types can be done through k-anonymization:
QuasiID = Degree

Employee	Degree
Samson	4
Delilah	2
Arthur	8
Alice	5
Bob	9
Merlin	1

2-anonymization $\Longrightarrow$

Employee	Degree
Merlin	[1-2]
Delilah	[1-2]
Samson	[4-5]
Alice	[4-5]
Bob	[8-9]
Arthur	[8-9]

If adversary has degree information about any individual it will match at least two individuals in published data.

Utilizing k-Anonymization Algorithms

- Anonymization with degree as an attribute will treat nodes with similar degrees as "close" to each other for merging.
- We might want "close"-ness to be defined in terms of graph connectivity.
- Create another attribute, which captures closeness in the graph.
- k-anonymize using this new attribute and the degree.
- Post-process results of k-anonymization to merge nodes whose degrees were merged, into supernodes in the graph.

General Class of Type-Anonymization Algorithms

While (! Anonymized)

1. Use Type-Histogram to determine the Type with lowest frequency.
2. Choose nodes N_h, N_l of highest and lowest degree of this type.
3. Perform one of the following in a suitable ratio:
   - Choice 1: Merge N_h with closest node/supernode of a Type with lesser than k nodes.
   - Choice 2: Merge N_l with node/supernode of the most similar Type with lesser than k nodes.
4. Label the merged node.
5. Update the histogram.

References