Securely Computing Clustering Coefficient for Outsourced Dynamic Encrypted Graph Data

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ComsNets 2021, Bengaluru, India

Importance of Graph

 # Social Medias

Increasing ↑

 # Users

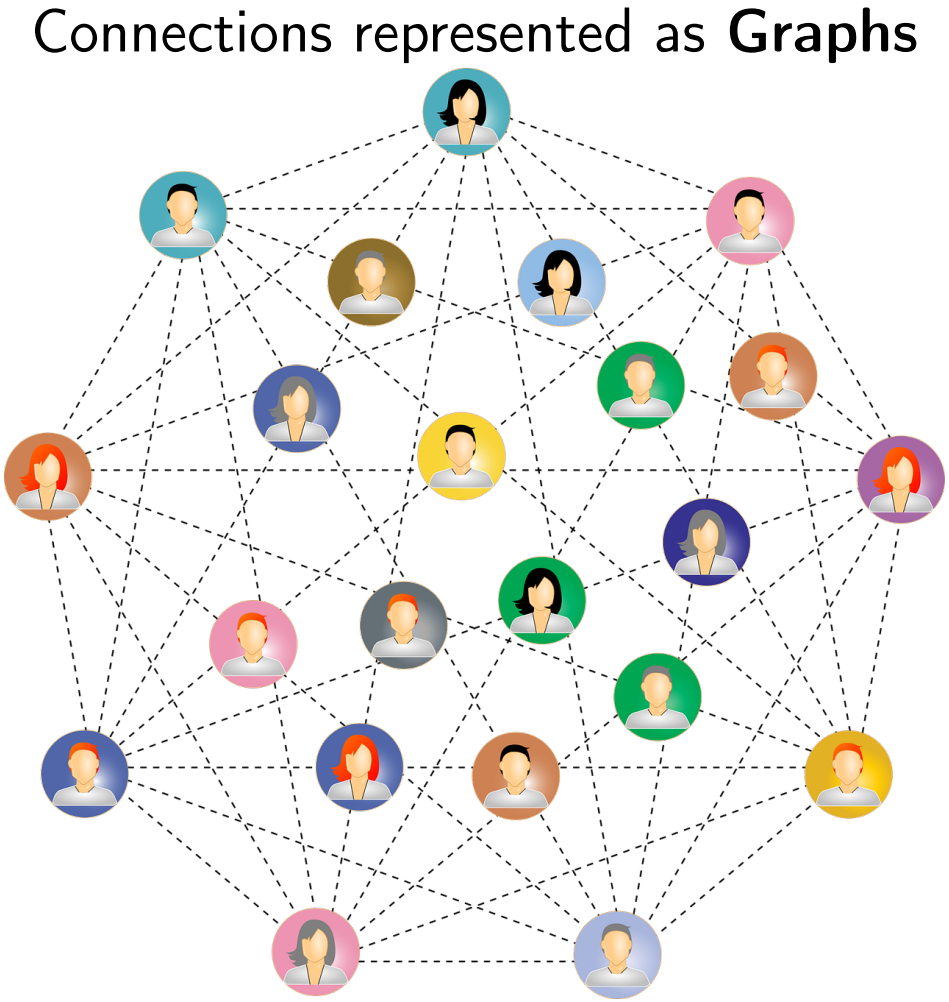
Increasing ↑

Importance of Graph

We Spending
More & More
Time

We Are getting
More & More
Connected

Importance of Graph



Dependency on Cloud Computing and Storage Services

Small and Medium Enterprises

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Small and Medium Enterprises

SME using Cloud Computing for *Cost & Security effectiveness*

- Easier to process requests and Faster to respond
- Data survivable probability Increases

Can we TRUST Cloud Service Providers?

TRUST?

Can we TRUST Cloud Service Providers?

TRUST?

Read Data

Sell Data

Hacked

Manipulation

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How to be SAFE?

How to be SAFE?

Data Anonymity

Ji et al. [?] showed that all the state-of-the-art anonymization schemes are vulnerable
to several or all of the modern structure-based de-anonymization attacks.

Fails

How to be SAFE?

How to be SAFE?

Encrypt Graph

Send Encrypted Graph

Store in cloud

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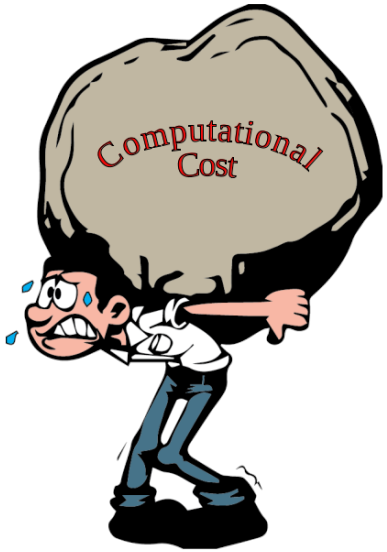

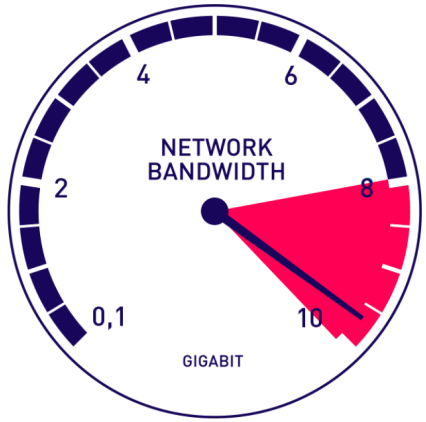

Cloud can't Search!

What we Need $\rightarrow$ Ability to Query

What we Need → Ability to Query

Encrypt Graph

Send Encrypted Graph

Store in cloud

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Encrypt Graph

Send Encrypted Graph

Store in cloud

1. User Sends

Query Token

2. Cloud Search

over Encrypted Graph

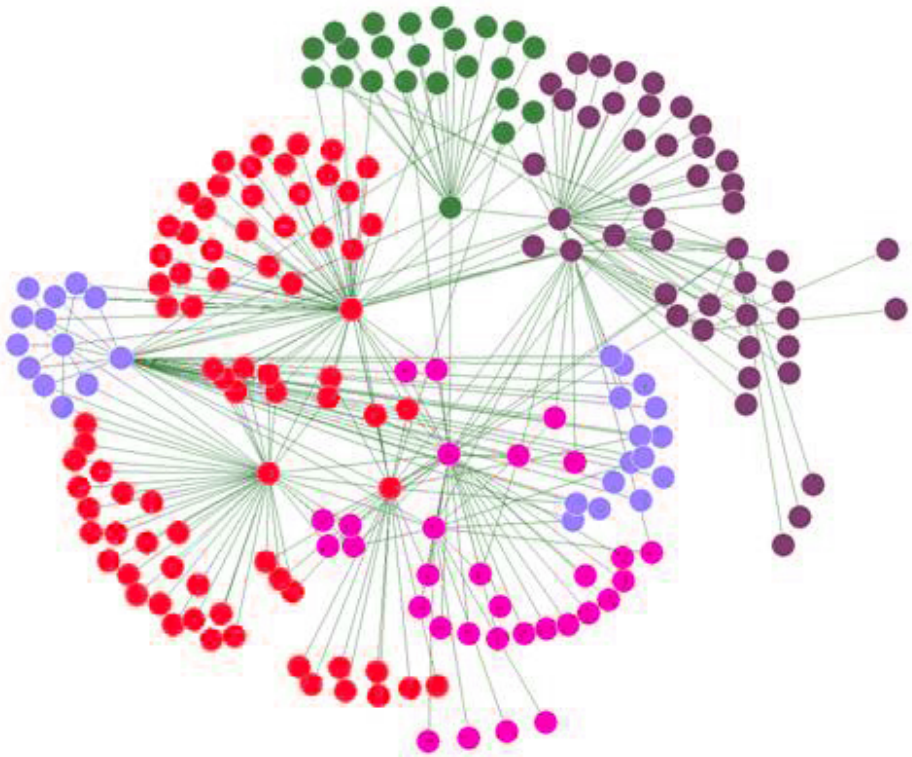
3.User received

Result

Type of Queries

- basic queries like vertex degree query, adjacency query [CK10].
- complex queries, the link prediction [SR19].
- The shortest distance query, that returns shortest distance between two given points [SMZ+18], [MKNK15], [WRD+17] etc.
- Xie and Xing [XX14] → clustering coefficient → used public key encryption scheme → makes the scheme inefficient for large datasets.

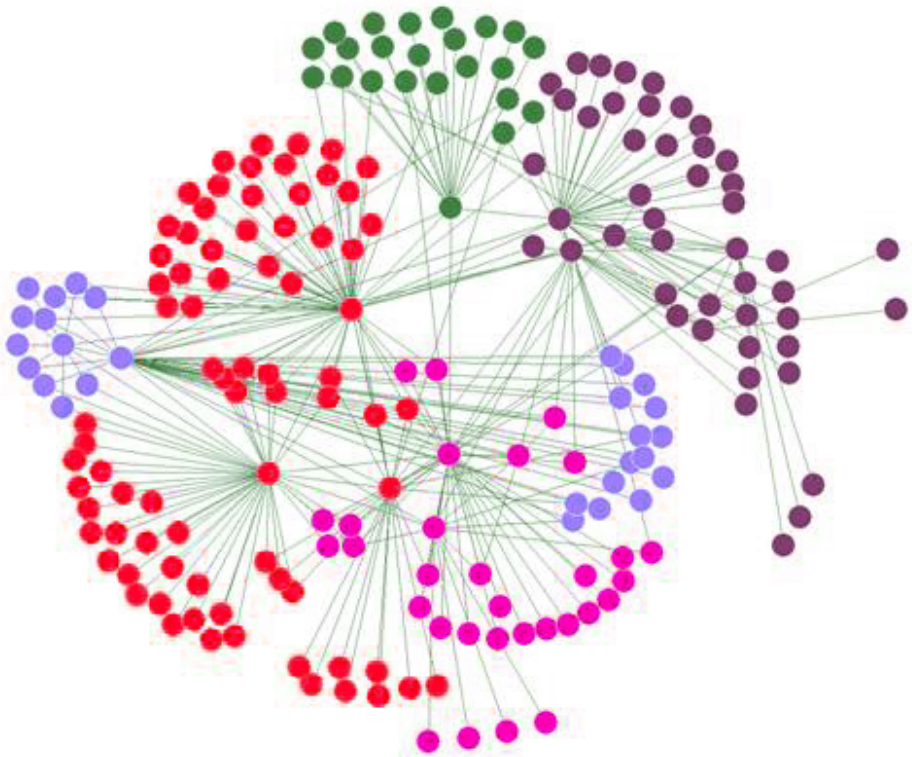
Clustering Coefficient: Concept



- In most real-world networks, nodes tend to create tightly knit groups characterized by a relatively high density of ties.
- The nodes $\in$ such a group have higher probability to be connected in the future.

Clustering Coefficient: Concept

Measure of the degree to which nodes in a graph associate with one another



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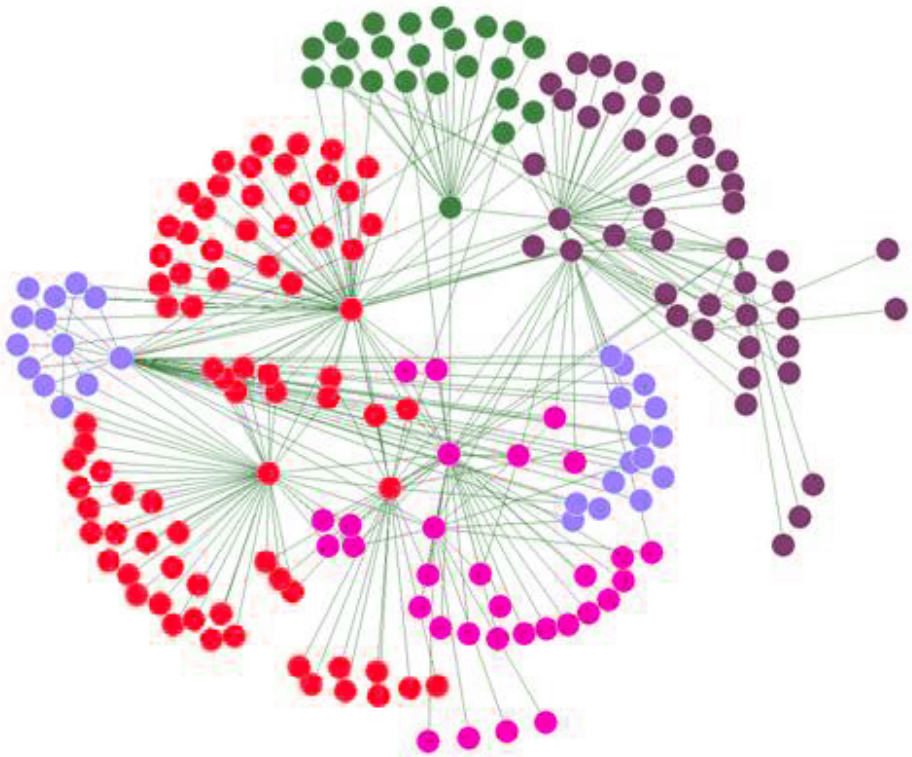

- In most real-world networks, nodes tend to create tightly knit groups characterized by a relatively high density of ties.
- The nodes $\in$ such a group have higher probability to be connected in the future.
- Important measure metric to study determine the structural properties
- High clustering coefficient $\Longrightarrow$ more prone to targeted attacks

Clustering Coefficient: Definition

Definition (Clustering Coefficient in Undirected Graph)

If the unweighted graph $G = (V, E)$ is undirected, **local** *clustering coefficient* for a node $v_i \in V$ is denoted by CC_i and defined as

$$CC_i = \frac{|\{e_{jk} : (v_j, v_k \in N_{v_i}) \wedge (e_{jk} \in E)\}|}{|N_{v_i}|(|N_{v_i}| - 1)/2}$$

$$= \frac{\text{Exising \# Connections among neighbors}}{\text{All Possible \# Connections among neighbors}}$$

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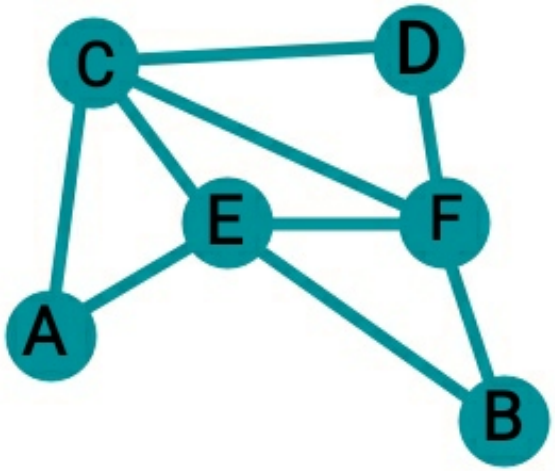
Example:



$$CC_E = \frac{3}{{}^4C_2} = \frac{3}{6} = 0.5$$

What We Contribute

- Design a novel graph encryption scheme *DCCE* that
  - performs clustering coefficient query.
  - The design is based on symmetric key encryption only.
  - Neighbor queries as well as edge queries on the same encrypted graph
  - Allows a new edge or vertex to be appended, making the scheme suitable for dynamic data.

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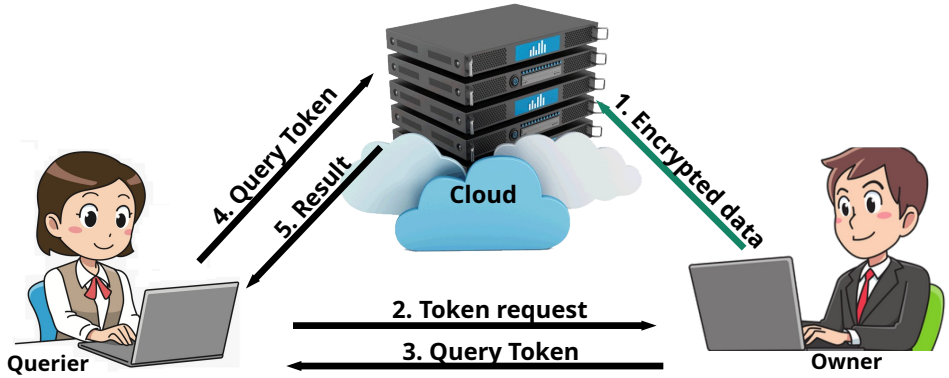
- Define the security in the random oracle model.Show that it is provably secure under the chosen-query attack.
- We implement a prototype,
  - Tested with multiple real-life *SNAP* [LK14] datasets.
  - results show that the scheme is practical even for a very large database.

System Model: Three Entities– Owner, Cloud and User.



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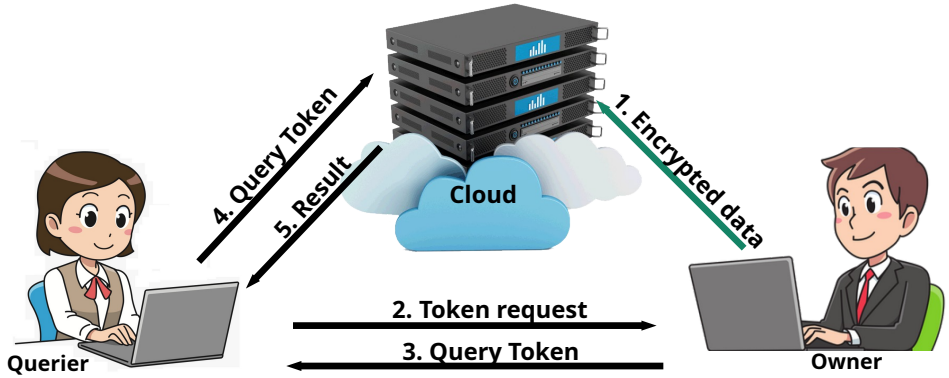
- Owns the database and Trusted
- Generates the required keys
- Encrypts graph and uploads.



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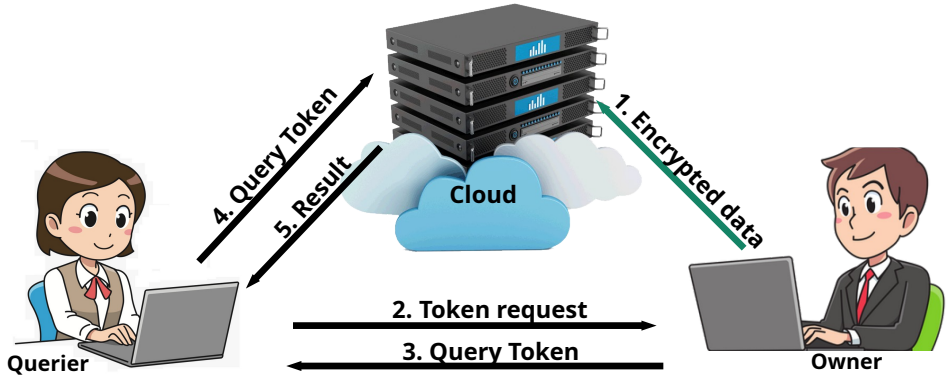

cloud

- *Honest-but-curious* cloud storage and computation service provider
- Performs a search over it on request from the user

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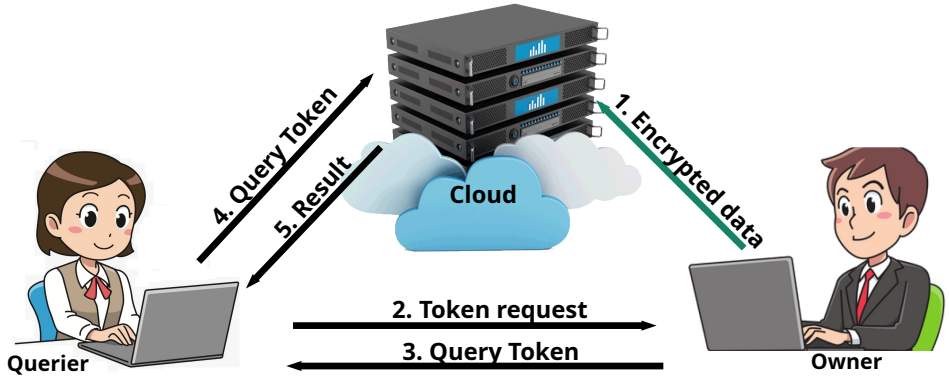

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- Takes a token from the owner
- Requests a query to the cloud

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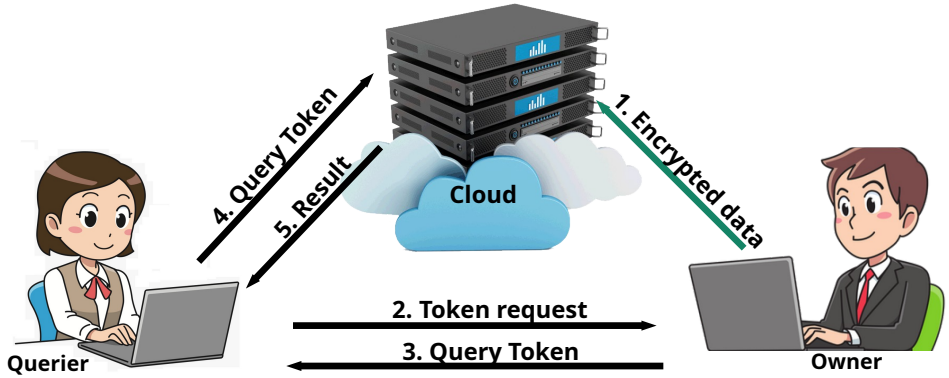

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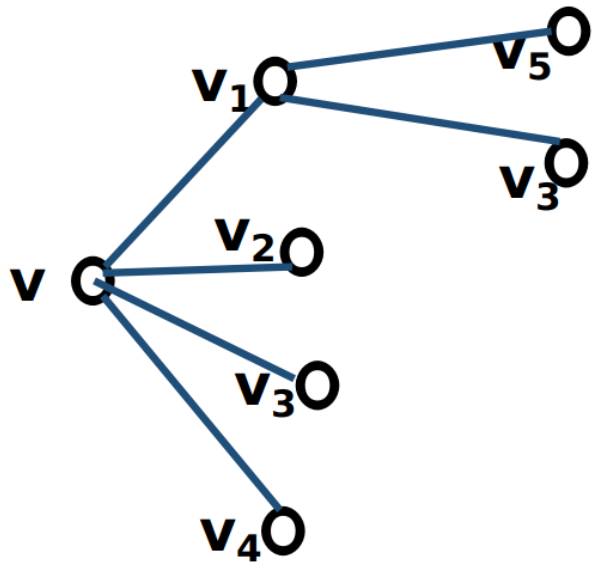
Assumption: Communication between entities $\rightarrow$ via secure channels

Our Approach to Calculate Clustering Coefficient

- Calculating triangles
- First find neighbors,
- Then find neighbor of neighbors
- Count the matches with first set of neighbors
- Final answer = $\frac{\text{total number of } \textit{existing} \text{ matches}}{\text{total number of } \textit{possible} \text{ matches}}$



Example

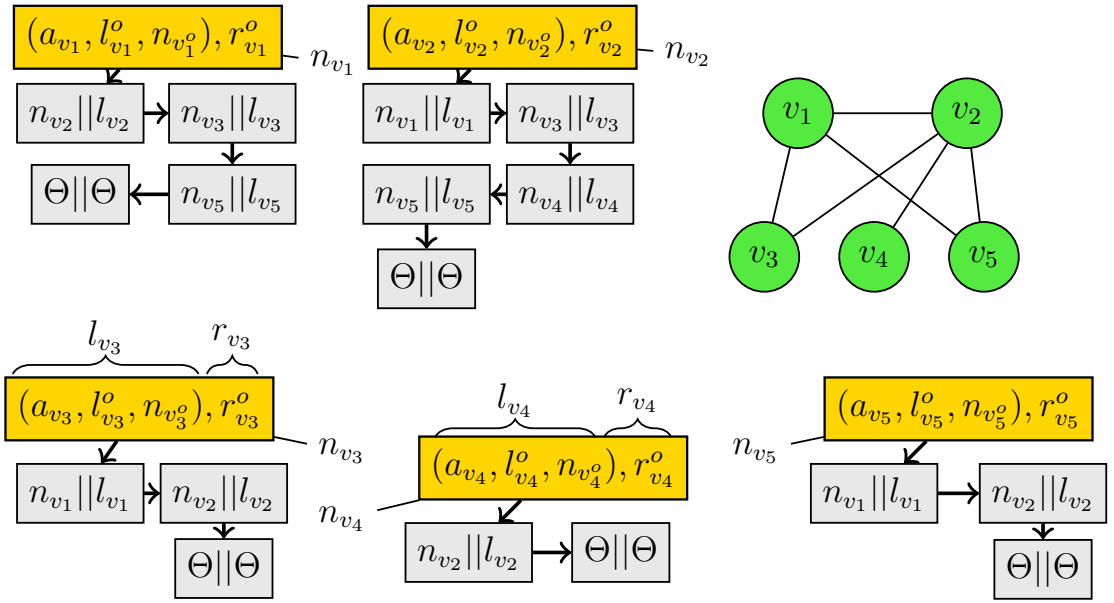
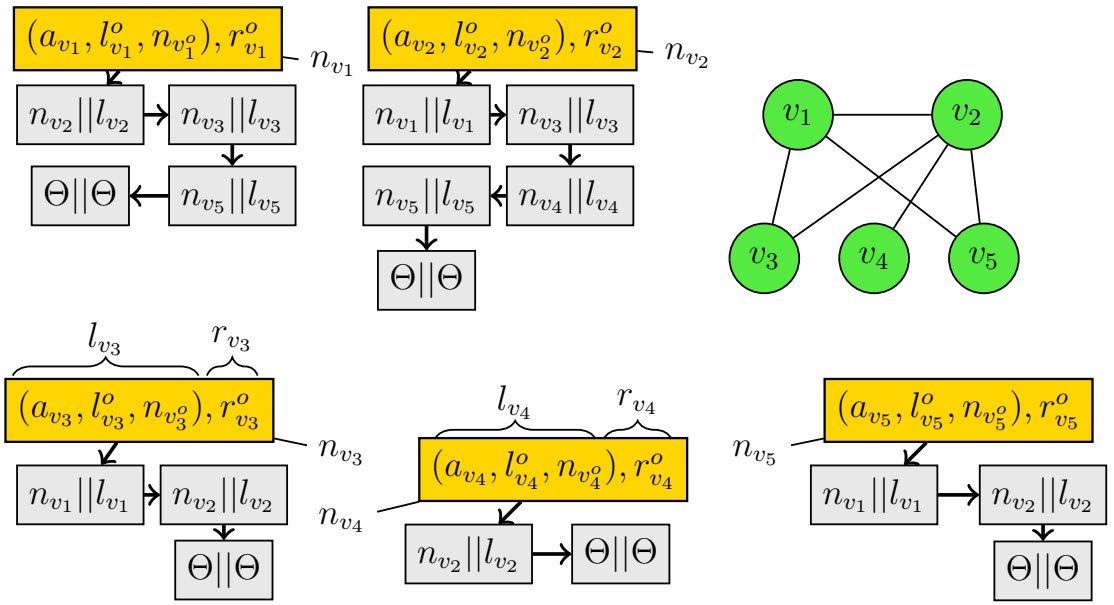


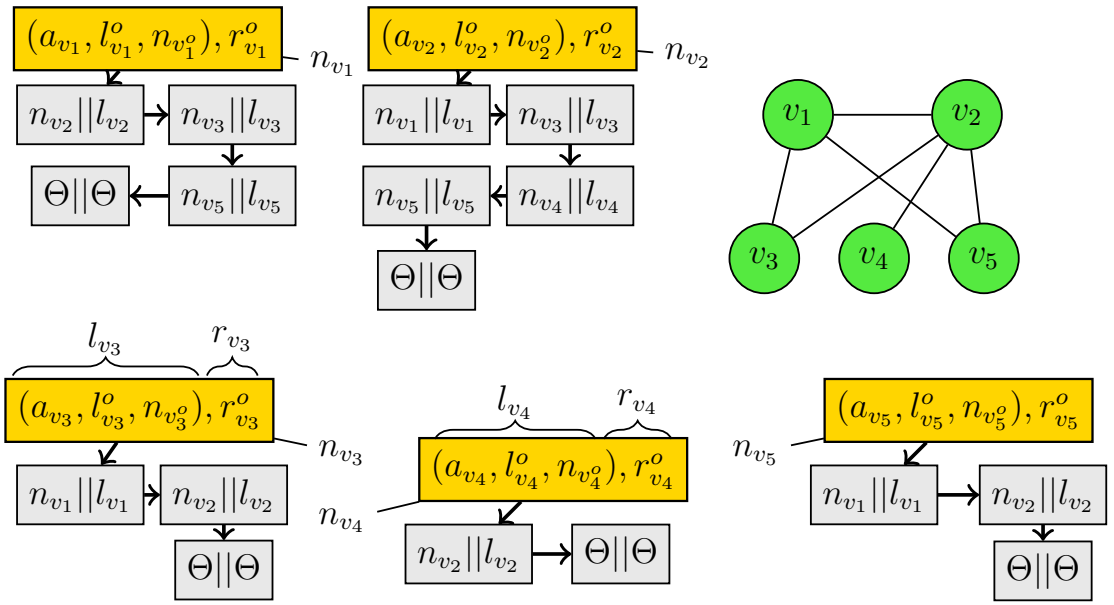
Figure: An example of what nodes store (before encryption)

- $n_v \leftarrow \mathtt{SE.Enc}(k_n, v)$;
- $T_E, T_V \leftarrow$ hash-tables corr. to edges & vertices
- $l_v \leftarrow$ to encrypt v in T_V
- $r_v \leftarrow$ to encrypt neighbors of v in t_E
- $n_v^o \leftarrow$ helps to traverse list of neighbors of v
- $\Theta \leftarrow$ null, termination symbol

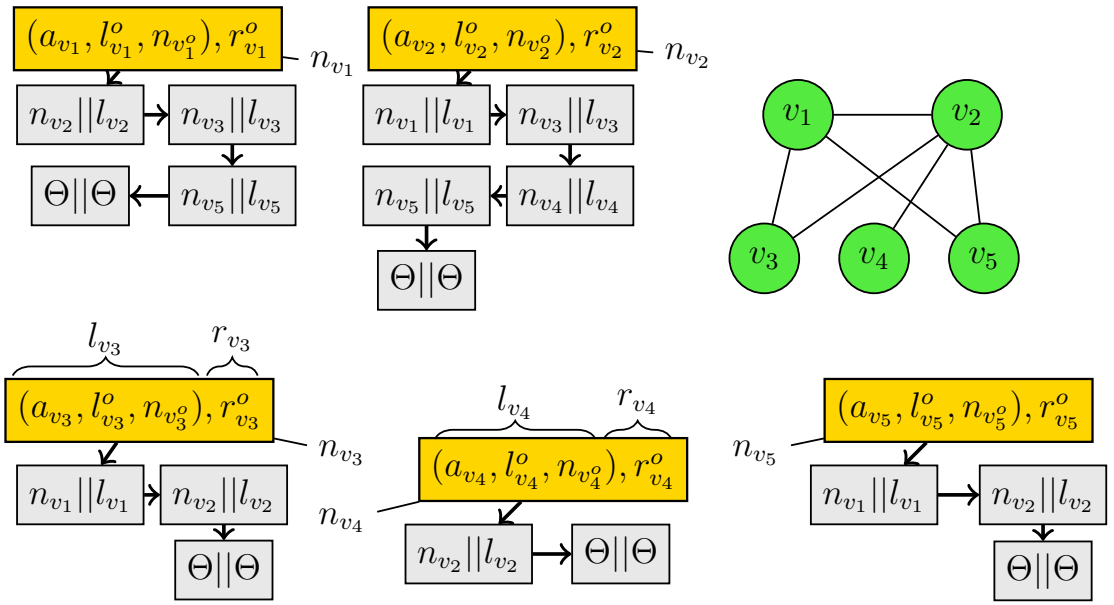
Example: Encryption



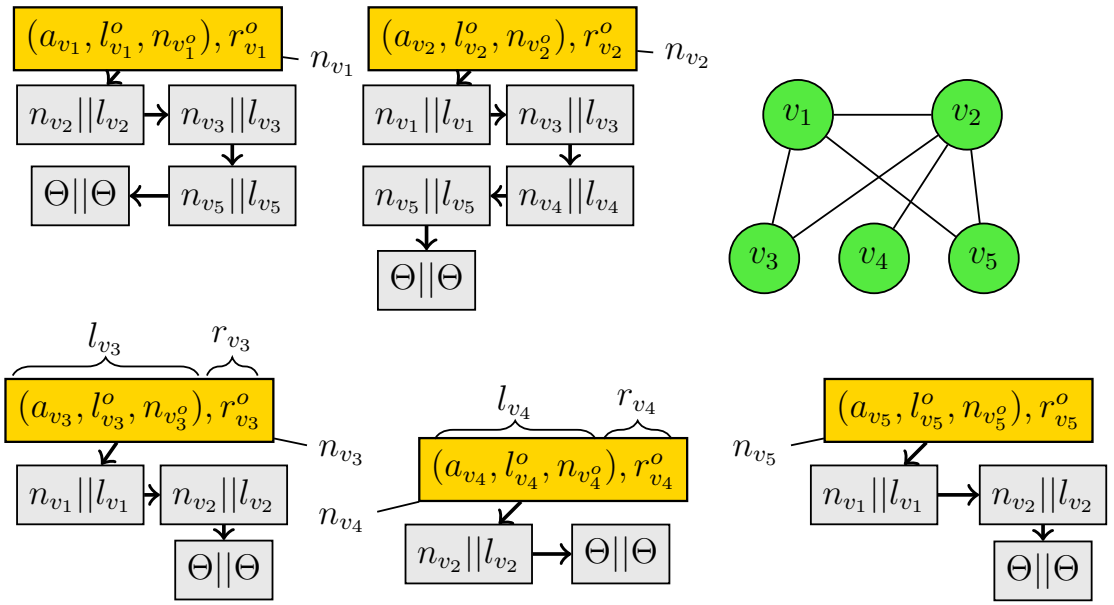
Example: Neighbor Query



Example: Clustering Coefficient Query



Example: Update



Security: Overview

Leakage Function $\mathcal{L} = \{\mathcal{L}_e, \mathcal{L}_n, \mathcal{L}_c, \mathcal{L}_{ae}, \mathcal{L}_{av}\}$.

- Initial dictionary construction:
  $\mathcal{L}_e(G) = \{|T_E|, \{n_v : v \in V\}, \{s_v : v \in V\}\}$,
- Neighbor query: $\mathcal{L}_n(v) = \{n_v, d_v, \{n_{v_i} : i = 0, \ldots, d_v\}\}$.
- Clustering coefficient query:

$$\mathcal{L}_c(v) = \{n_v, d_v, \{(n_{v_i}, d_{v_i}, \mathcal{L}_n(v_i)) : v_i \in N_v\}\}$$

- Adding a vertex: $\mathcal{L}_{av}(v) = \{key, key^o, g_v\}$
- Adding an Edge:
  $\mathcal{L}_{ae}(u, v) = \{key_u, key'_u, g_u, key_v, key'_v, g_v, \mathcal{L}_n(u), \mathcal{L}_n(v)\}$

Theorem

If F, P, G, H and $\mathtt{SE}$ is a PRG, a PRP, a PRP, a hash functions and a CPA-secure symmetric key encryption respectively, then $\mathtt{DCCE}$ is $\mathcal{L}$-secure against adaptive dynamic chosen-query attacks, in random oracle model.

Implementation Environment

System Configaration

- Language Used: C++
- Processor: Intel Core i7-4770 CPU, 8-core, 3.40GHz.
- Operating System: Ubuntu 16.04 LTS 64-bit, with 8GB RAM.

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Crypto functions

- *cryptopp* library
- $P \leftarrow$ *HMAC*; $F \leftarrow$ *Salsa20*; $H \leftarrow$*SHA-256*; $SE \leftarrow$*AES*

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Dataset

- Real-world *SNAP* [LK14] datasets $\rightarrow$ a collection of large networks
- 'ca-HepPh', 'email-Enron', 'loc-Gowalla', and 'roadNet-CA'
- # nodes: 12,008, 36,692, 196,591, 1,965,206
- # edges: 118,521, 183,831, 950,327, 2,766,607

Encryption Time

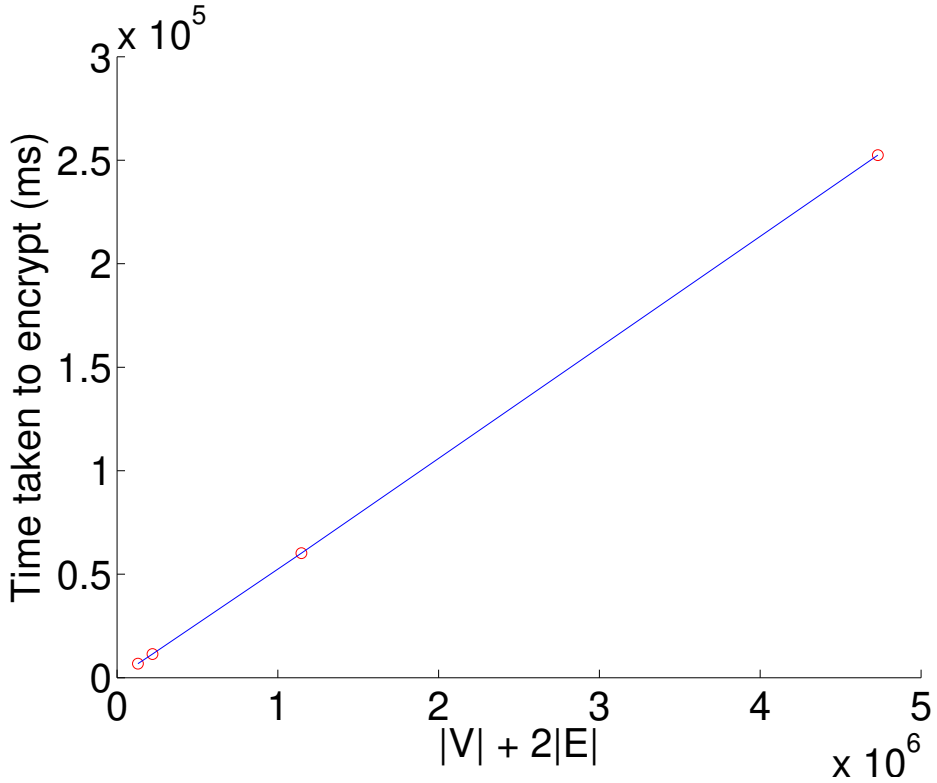
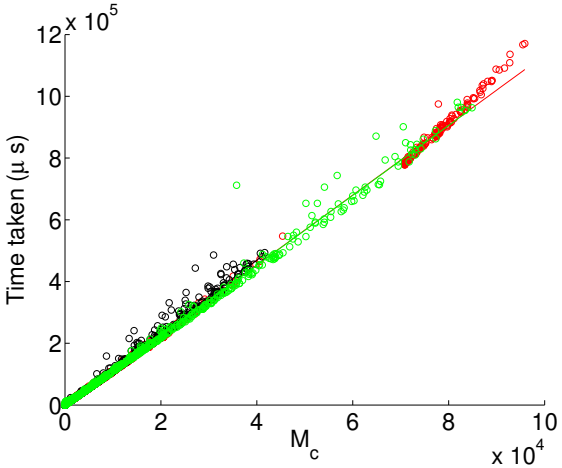


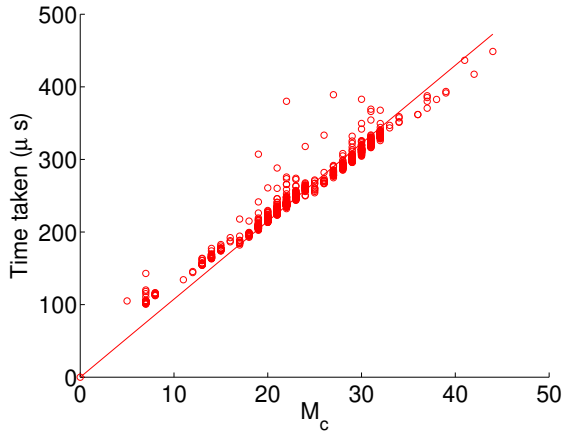
Figure: Encryption Time on different datasets

- Encrypt time $\propto M_e = (|V| + 2|E|)$.
- $M_e = 53.3\mu s$, in our case

Clustering coefficient query Time



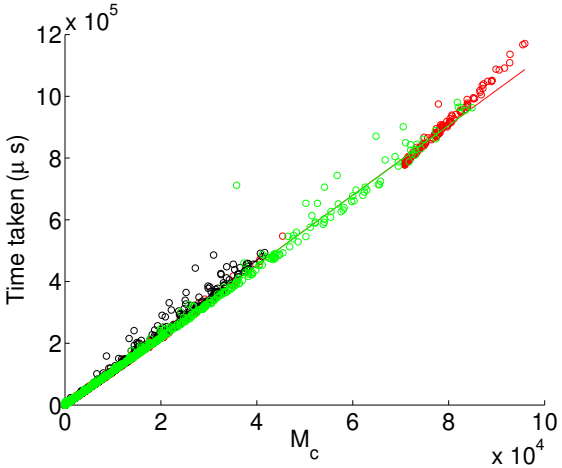
(a) HepPh, Enron, Gowalla



(b) roadNet-CA

Figure: CC Query time on different datasets

Clustering coefficient query Time



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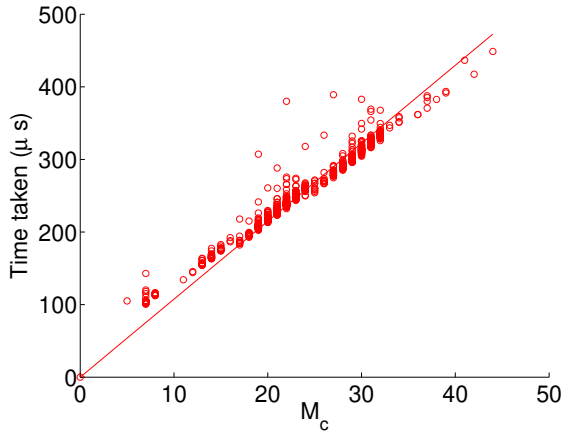

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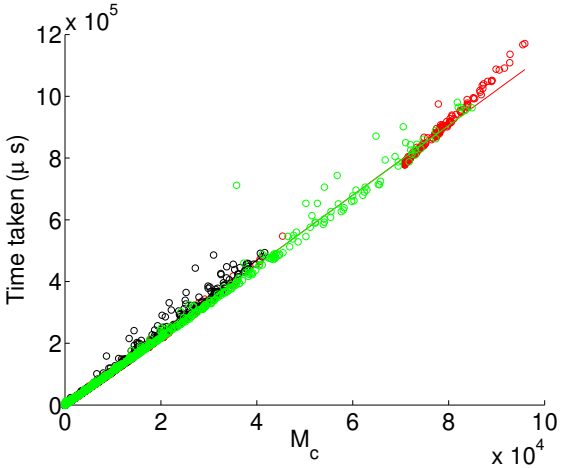
Figure: CC Query time on different datasets

- query time for $v \propto M_c = (4|N_v| + \sum_{u \in N_v} |N_u|)$
- average values of M_cs are $11.33\mu s$, $11.72\mu s$, $11.32\mu s$, and $10.76\mu s$

Clustering coefficient query Time



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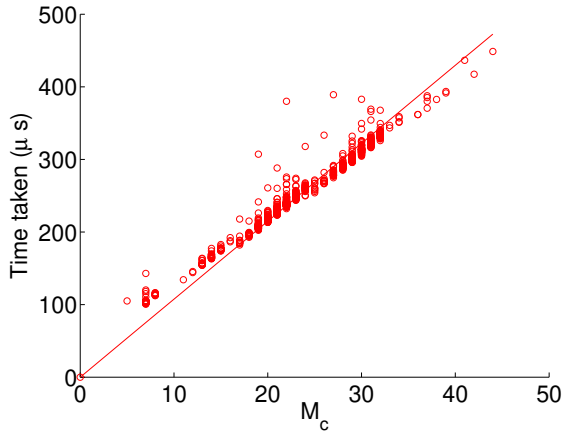

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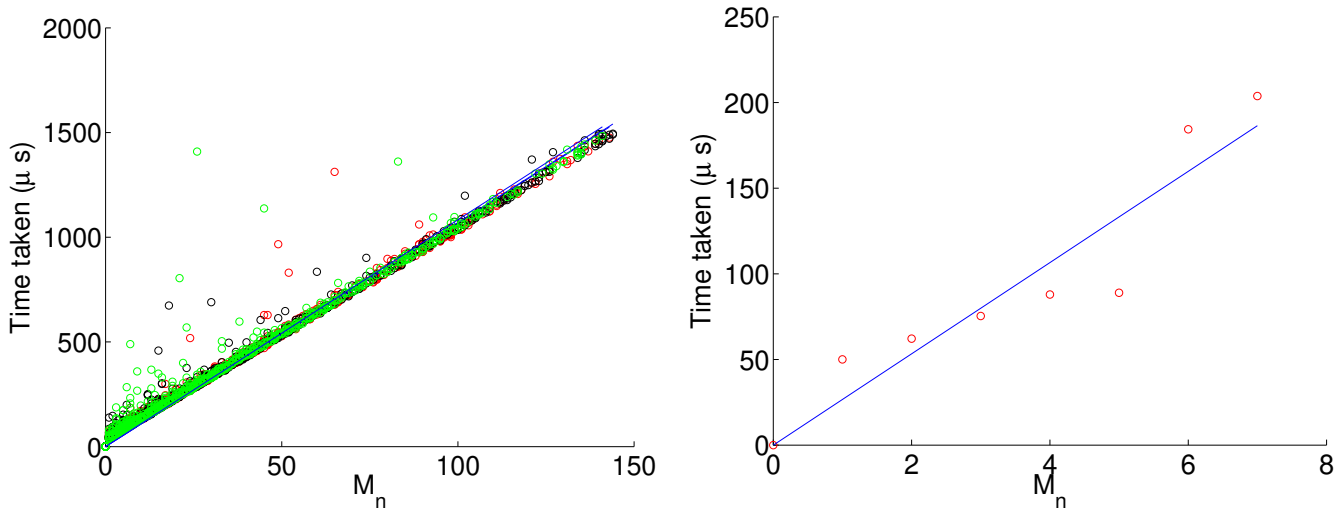
Improvement over PKE based Scheme

- **Our scheme**: 196,591 vertices and 950,327 edges, $\rightarrow$ $1.2s$
- **[XX14]**: 62 vertices and 159 edges, $18.77s$.
- Huge improvement $\rightarrow$ use of symmetric key encryption and efficient data structure.

Neighbor Query time



(a) HepPh, Enron, Gowalla (b) roadNet-CA

Figure: Neighbor Query time on different datasets

- Time taken by the cloud $\propto M_n = |N_v|$ for v.
- M_n is 10.40μs, 10.46μs, 10.54μs, and 23.68μs respectively.

Update time

- Addition of a vertex $\rightarrow$ constant for any vertex.
- The time taken to add a vertex = $69\mu s$.
- Adding edge $\rightarrow$ constant time.
- The time taken to add an edge = $124\mu s$ for the client.

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Thank You!

Questions?