Methods and Applications of Network Sampling

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What matters. Where it matters.

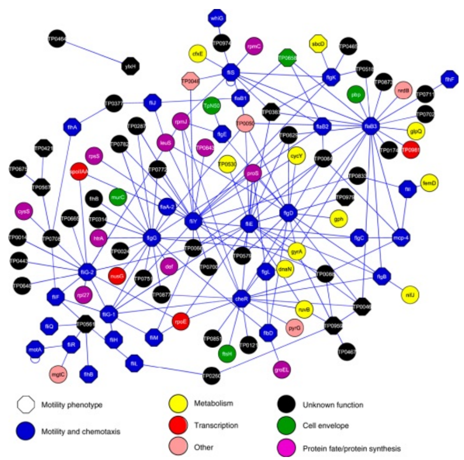
Tutorial Outline

- Introduction (5 minutes)
  - Motivation, Challenges
- Sampling Background (10 minutes)
  - Assumption, Definition, Objectives
- Network Sampling methods (full access, restricted access, streaming access)
  - Estimating nodal or edge characteristics (30 minutes)
  - Sampling representative sub-networks (30 minutes)
  - Sampling and counting of sub-structure of networks (30 minutes)
- Conclusion and Q/A (15 minutes)

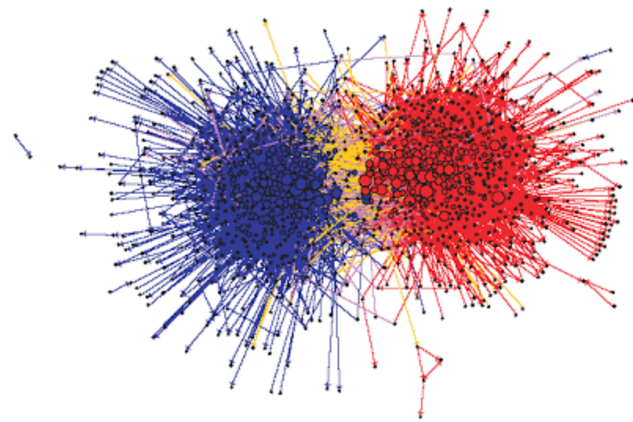
Introduction

motivation and challenges

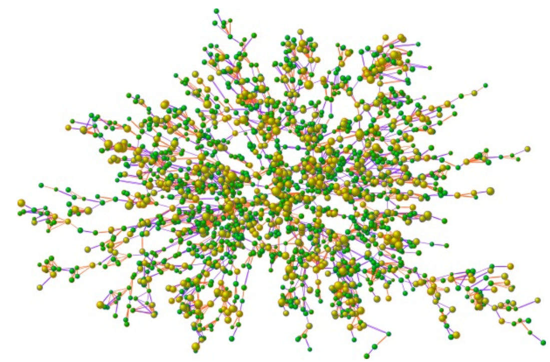
Network analysis in different domains



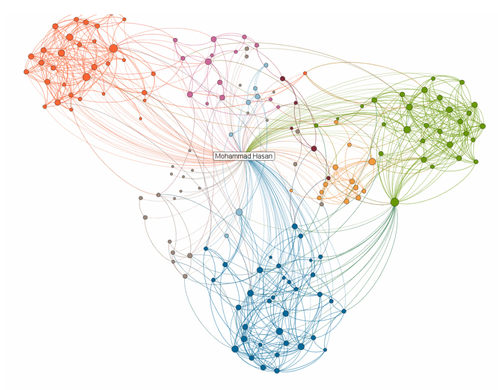
Protein-Interaction network



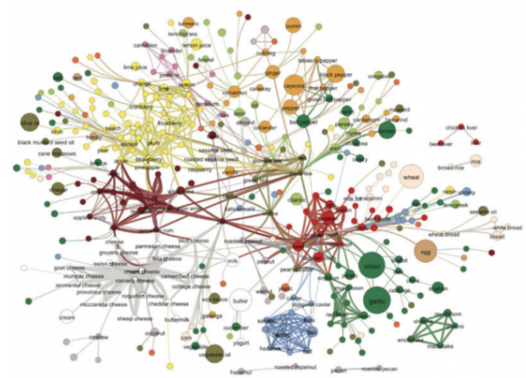
Political Blog network



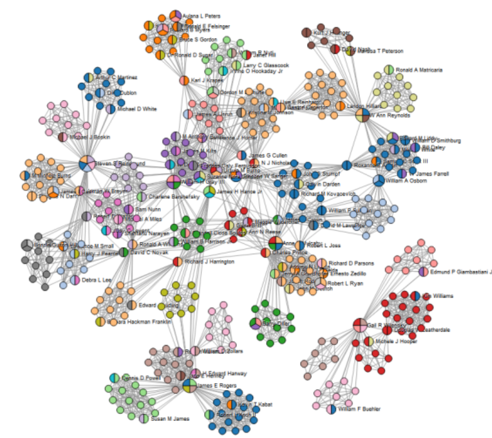
Social network



LinkedIn network

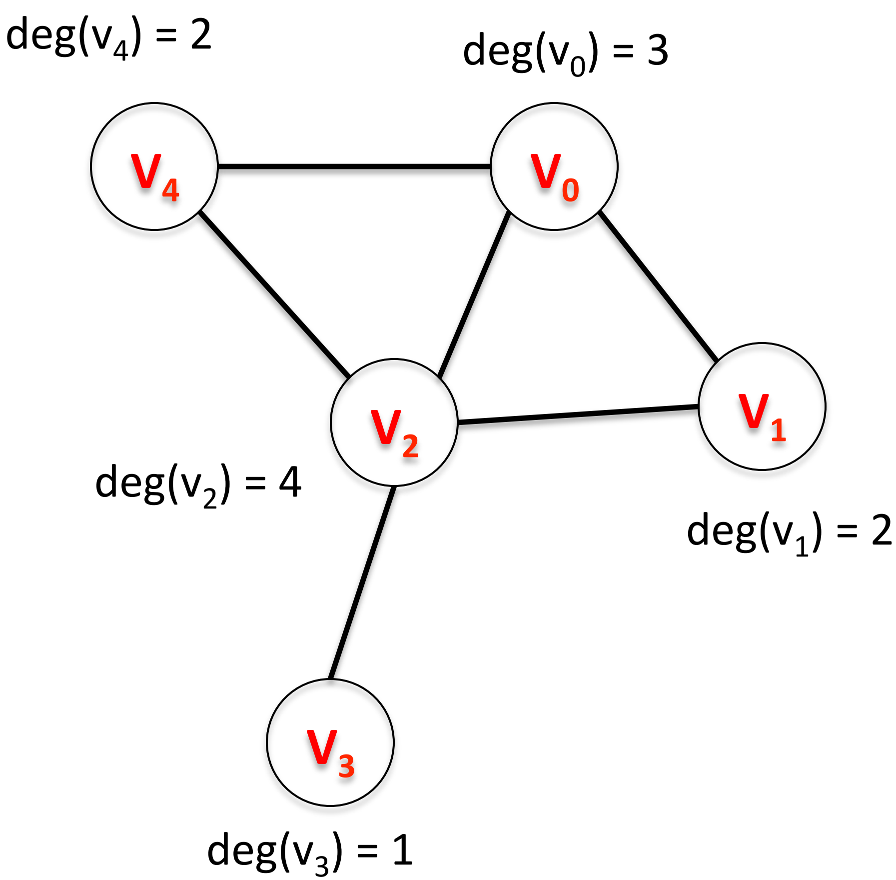


Food flavor network



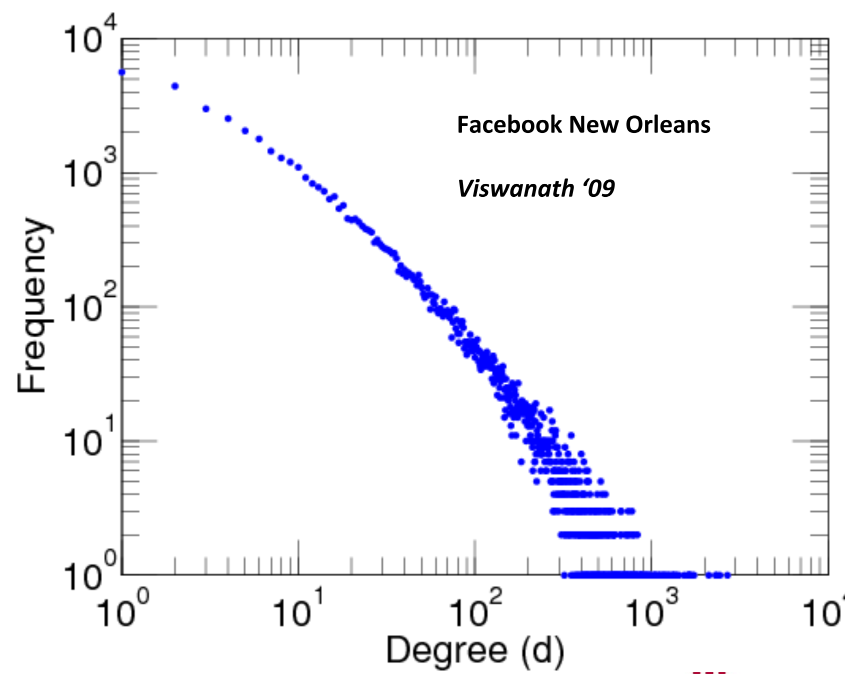
Professional Network

Network characteristics



|V| = 5 vertices
|E| = 6 edges

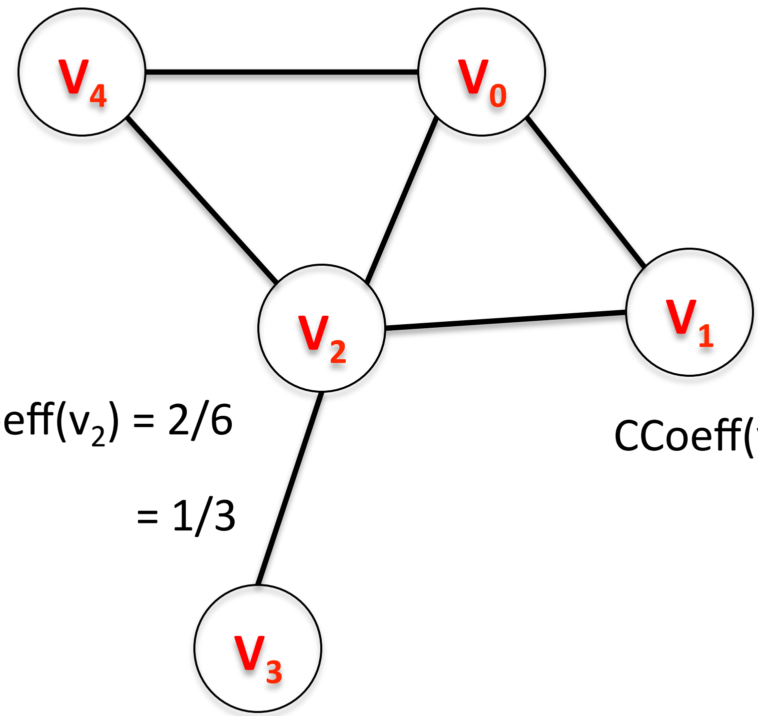
Avg. degree = 2.4



Network characteristics

CCoeff(v_4) = 1

CCoeff(v_0) = 2/3



CCoeff(v_2) = 2/6

= 1/3

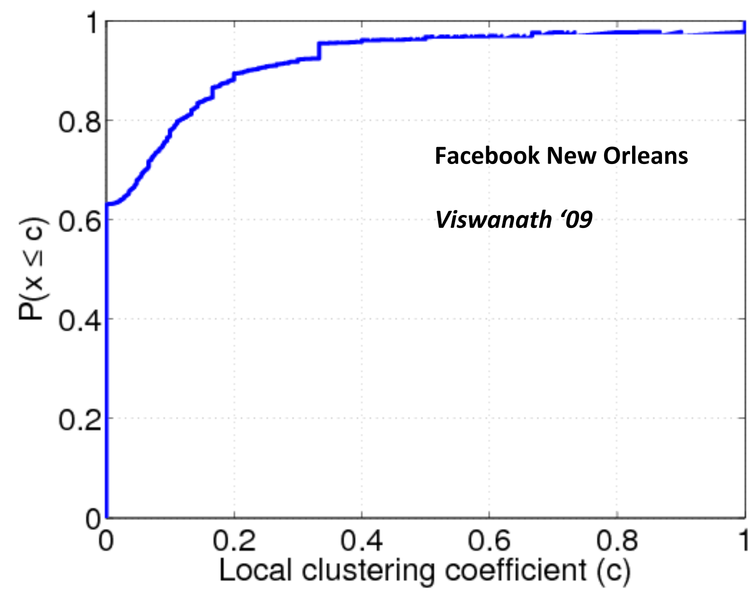
CCoeff(v_1) = 1

CCoeff(v_3) = 0

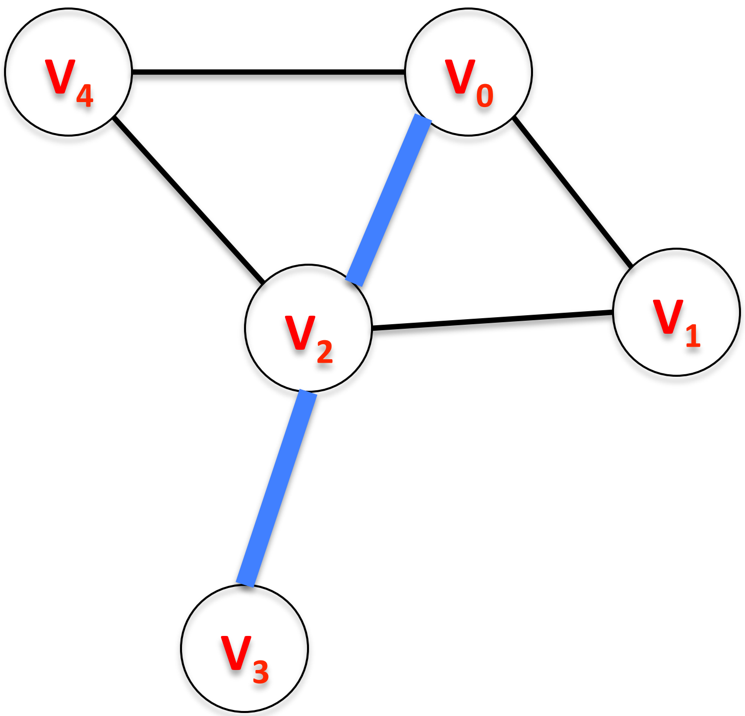
|V| = 5 vertices
|E| = 6 edges

Avg. Local Clustering Coeff = 0.6

Global Clustering Coeff:
= (3# triangles) / # triplets*
= 0.55



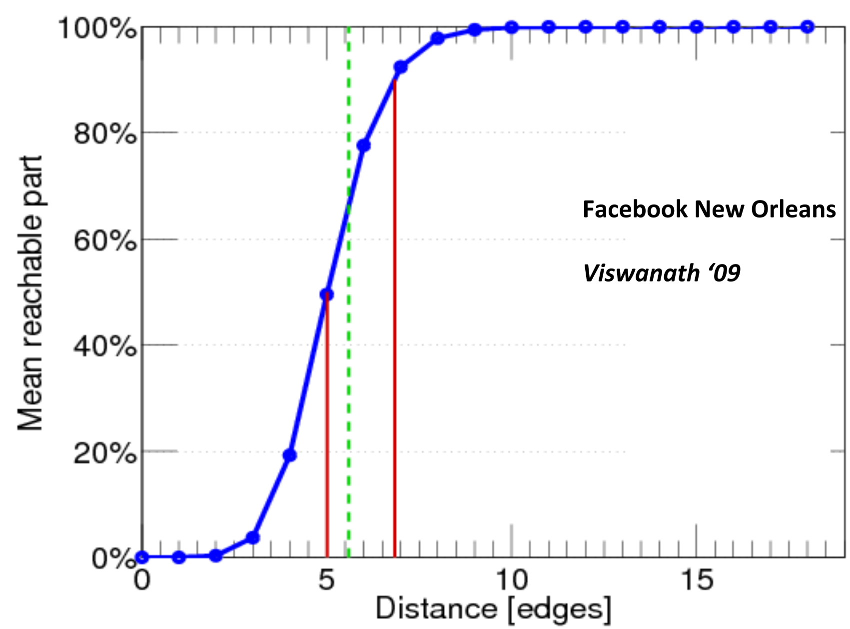
Network characteristics



|V| = 5 vertices
|E| = 6 edges

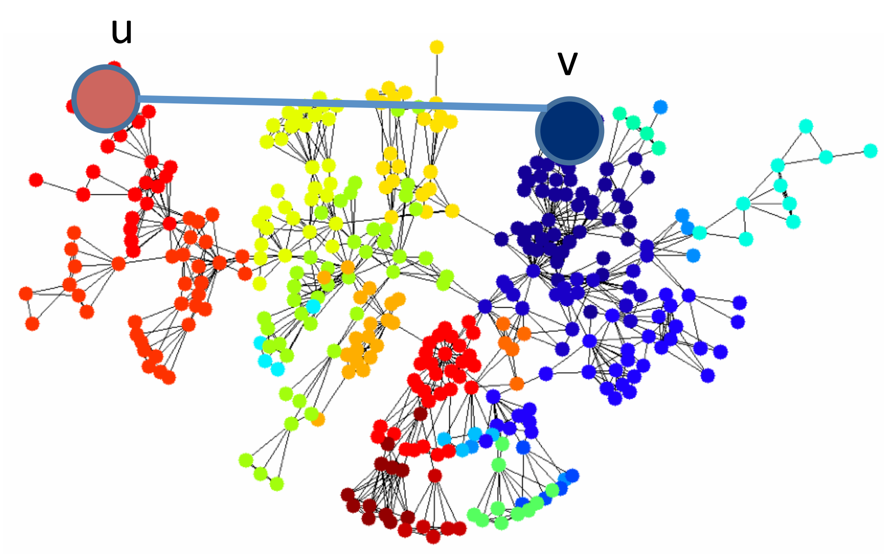
Avg. Shortest Path Length = 1.4

Diameter = 2



Network analysis tasks

- Study the node/edge properties in networks
  - E.g., Investigate the correlation between attributes and local structure
  - E.g., Estimate node activity to model network evolution
  - E.g., Predict future links and identify hidden links

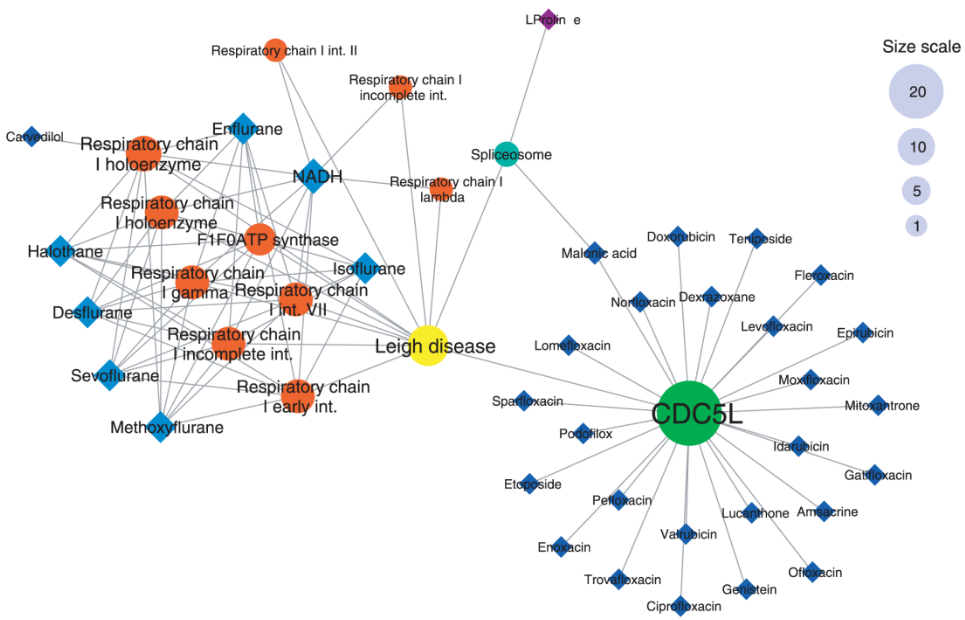


Communities of physicists that work on social networks

Link Prediction:
What is the probability that u and v will be connected in future?

Network analysis tasks (cont.)

- Study the connectivity structure of networks and investigate the behavior of processes overlaid on the networks
  - E.g., Estimate centrality and distance measures in communication and citation networks
  - E.g., Identify communities in social networks
  - E.g., Study robustness of physical networks against attack

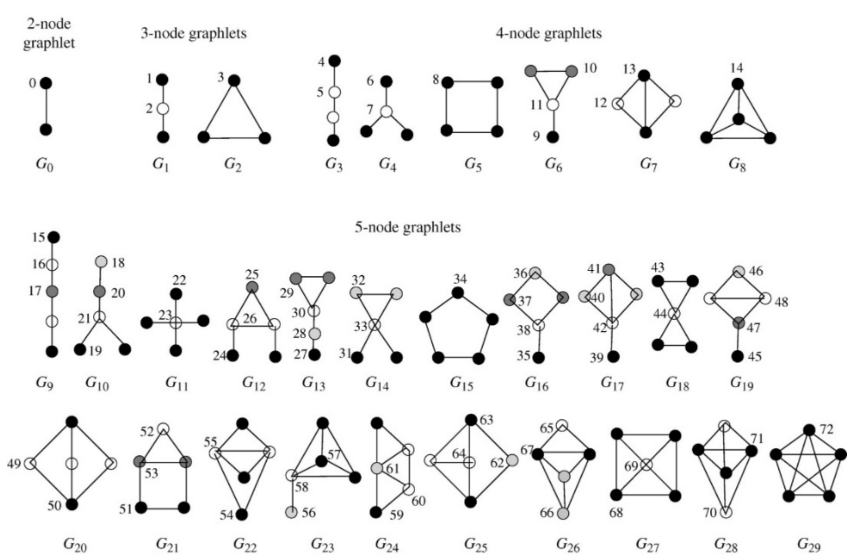


Centrality analysis on heterogeneous networks that include nodes for diseases, proteins and drug can be used to identify new pharmacology study.

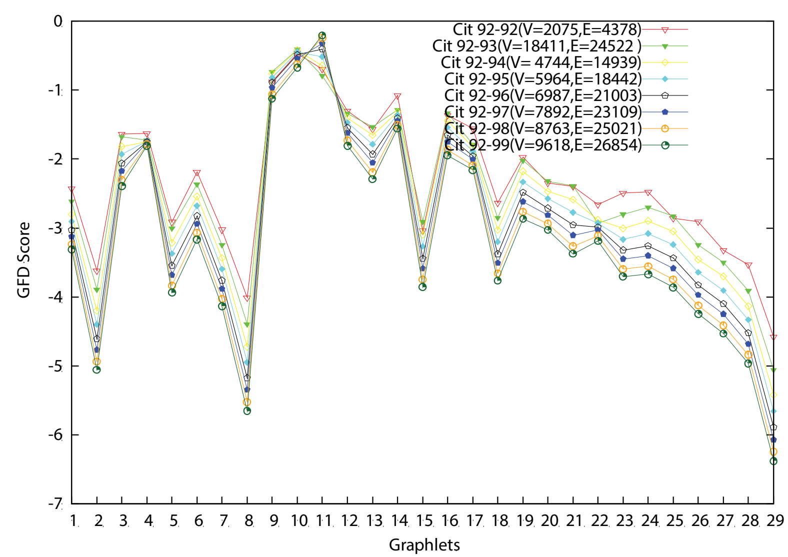
Source: Modularity in Protein Complex and Drug Interactions Reveals New Polypharmacological Properties, Jose C. Nacher mail, and Jean-Marc Schwartz, *PloS One, 2012*

Network analysis tasks

- Study local topologies and their distributions to understand local phenomenon
  - E.g., Discovering network motifs in biological networks
  - E.g., Counting graphlets to derive network “fingerprints”
  - E.g., Counting triangles to detect Web (i.e., hyperlink) spam



Graphlets



Graphlet Frequency Dist.

Computational complexity makes analysis difficult for very large graphs

- Best time complexities for various tasks: vertex count *(n)*, edge count *(m)*
  - Computing centrality metrics $O(mn)$
  - Community Detection using Girvan-Newman Algorithm, $O(m^2 n)$
  - Triangle counting $O(m^{1.41})$
  - Graphlet counting for size k $O(n^k)$
  - Eigenvector computation $O(n^3)$
    - Pagerank computation uses eigenvectors
    - Spectral graph decomposition also requires eigenvalues

For graphs with billions of nodes, none of these tasks can be solved in a reasonable amount of time!

Other issues for network analysis

- Many networks are too **massive** in size to process offline
  - In October 2012, Facebook reported to have 1 billions users.
    Using 8 bytes for userID, 100 friends per user, storing the raw edges will take 1 Billions x 100 x 8 bytes = *800 GB*
- Some network structure may **hidden** or inaccessible due to privacy concerns
  - For example, some networks can only be crawled by accessing the one-hop neighbors of currently visiting node – it is not possible to query the full structure of the network
- Some networks are **dynamic** with structure changing over time
  - By the time a part of the network has been downloaded and processed, the structure may have changed

Network sampling approaches

- We can sample a set of vertices (or edges) and estimate nodal or edge properties of the original network
  - E.g., Average degree and degree distribution

Task 1

- Instead of analyzing the whole network, we can sample a small subnetwork similar to the original network
  - Goal is to maintain global structural characteristics as much as possible e.g., degree distribution, clustering coefficient, community structure, pagerank

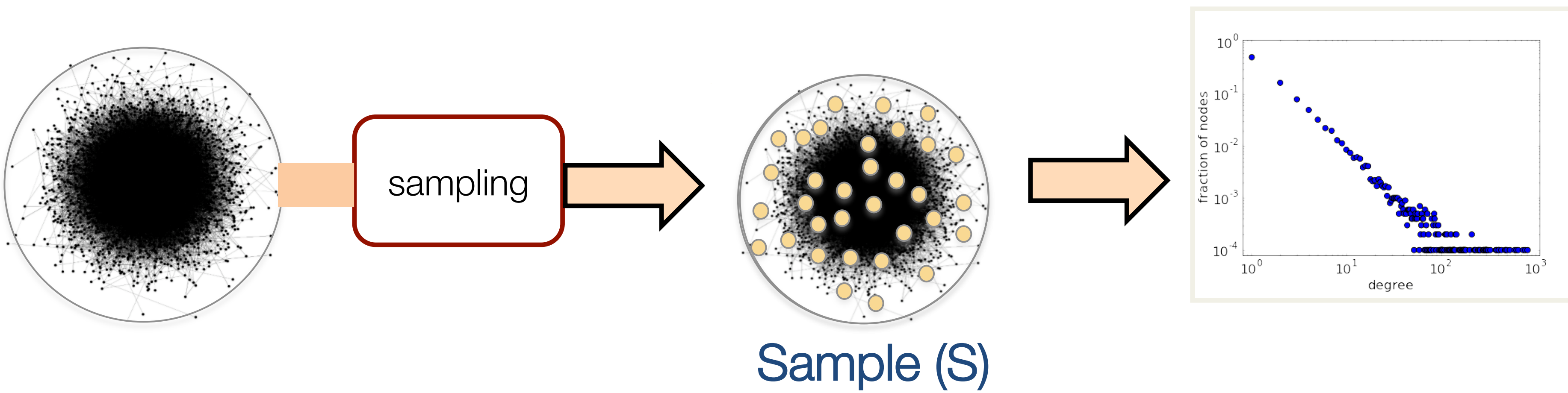
Task 2

- We can also sample local substructures from the networks to estimate their relative frequencies or counts
  - E.g., sampling triangles, graphlets, or network motifs

Task 3

Sampling objectives (Task 1)

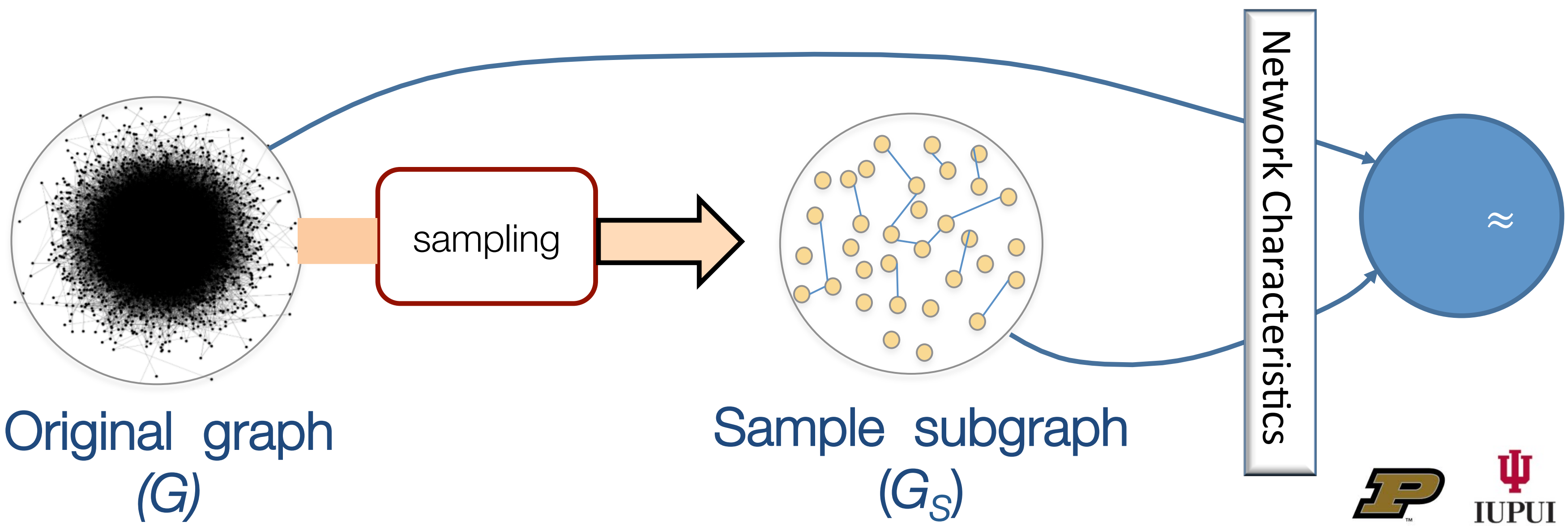
- Estimate network characteristics by sampling vertices (or edges) from the original networks
- Population is the entire vertex set (for vertex sampling) and the entire edge set (for edge sampling)
- Sampling is usually with replacement



Estimating degree distribution of the original network

Sampling objectives (Task 2)

- Goal: From *G*, sample a subgraph with *k* nodes which preserves the value of key network characteristics of *G*, such as:
  - Clustering coefficient, degree Distribution, diameter, centrality, and community structure
  - Note that, the sampled network is smaller, so there is a scaling effect on some of the statistics; for instance, average degree of the sampled network is smaller
- Population: All subgraph of size *k*



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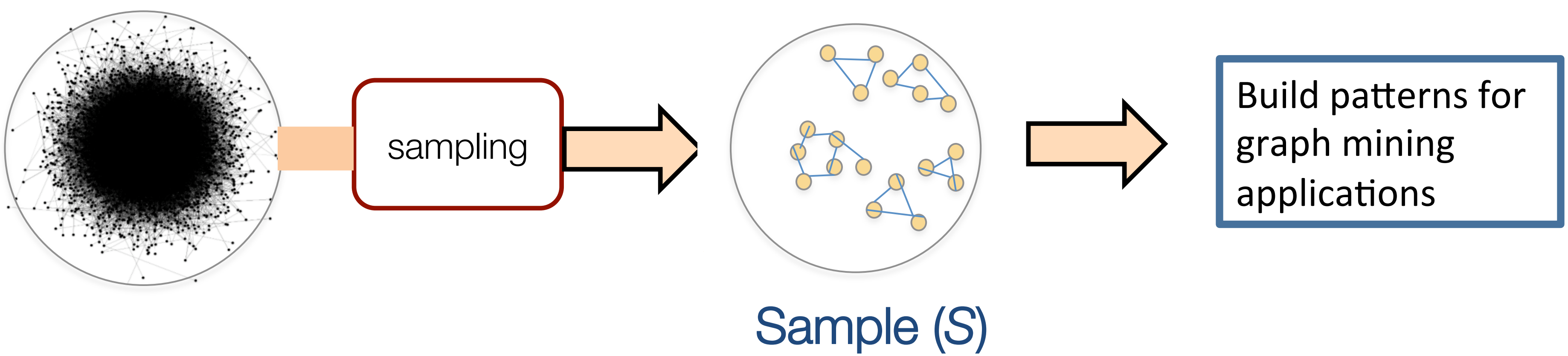
Sampling objective (Task 3)

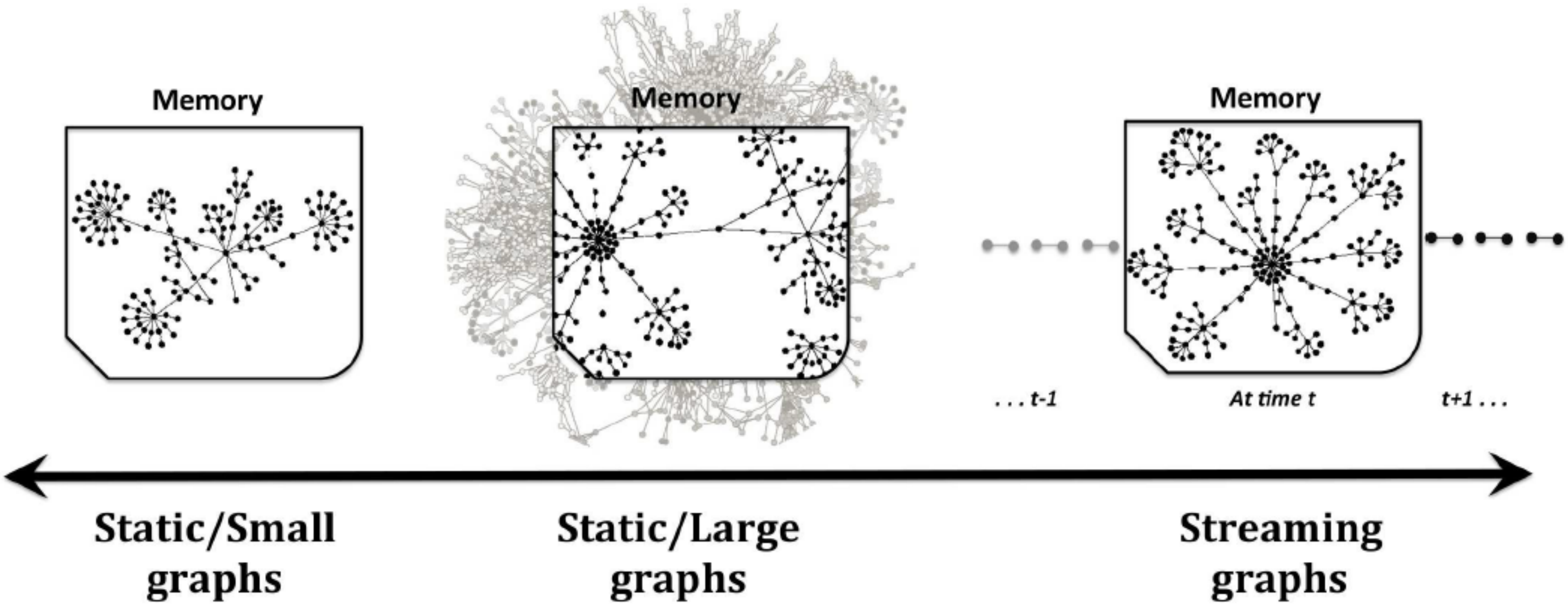
- Sample sub-structure of interest
  - Find frequent induced subgraph (network motif)
  - Sample sub-structure for solving other tasks, such as counting, modeling, and making inferences



Sampling scenarios

- **Full access assumption**
  - The entire network is visible
  - A random node or a random edge in the network can be selected
- **Restricted access assumption**
  - The network is hidden, however it supports crawling, i.e. it allows to explore the neighbors of a given node.
  - Access to one seed node or a collection of seed nodes are given.
- **Streaming access assumption (limited memory and fast moving data)**
  - In the data stream, edges arrives in an arbitrary order (arbitrary edge order)
  - In the data stream, edges incident to a vertex arrives together (incident edge order)
  - Stream assumption is particularly suitable for dynamic networks

Sampling scenarios (cont.)



- For static and/or small network, computation model can assume that the entire network is in the memory
- For large but static network, part of the network can be loaded in the memory, but the entire network remains in disk or graph database
- Streaming scenario works well for both dynamic and large networks

Sampling methods

methodologies, comparison, analysis

TASK 1

Estimating node/edge properties of the original network

Estimate node/edge properties in original network

Sample representative subgraph/subnetwork

Estimate frequency of subgraph patterns

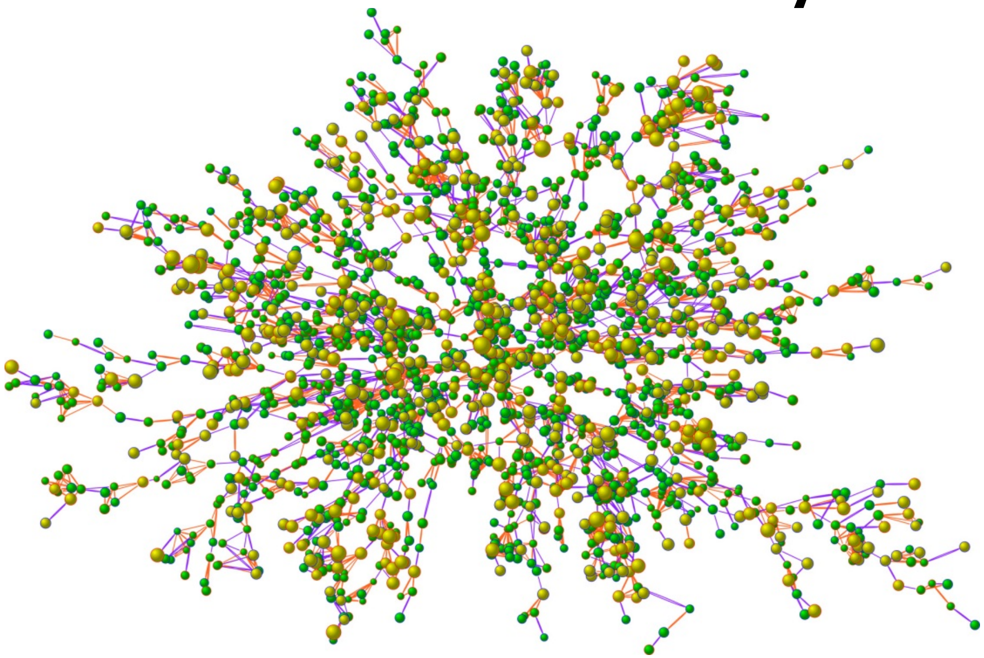
Data Access Assumption

	Task 1	Task 2	Task 3
Full Access	✓		
Restricted Access			
Data Stream Access			

Sampling Objective

Sampling methodology

Real-life Application of such analysis task!



The New England Journal of Medicine. The study's authors suggest that obesity isn't just spreading; rather, it may be contagious between people, like a common cold.

Read more: http://www.time.com/time/health/article/0,8599,1646997,00.html#ixzz2XAtfg02V

- Red borders are women, blue borders are men
- Size of a node represents BMI
- Orange nodes are obese, and green nodes are normal
- Purple links are close genetic connection
- Gray node denotes non-genetic ties (friends, spouse, co-workers)

How to conduct the same analysis on Facebook data where *n=1 billion*?

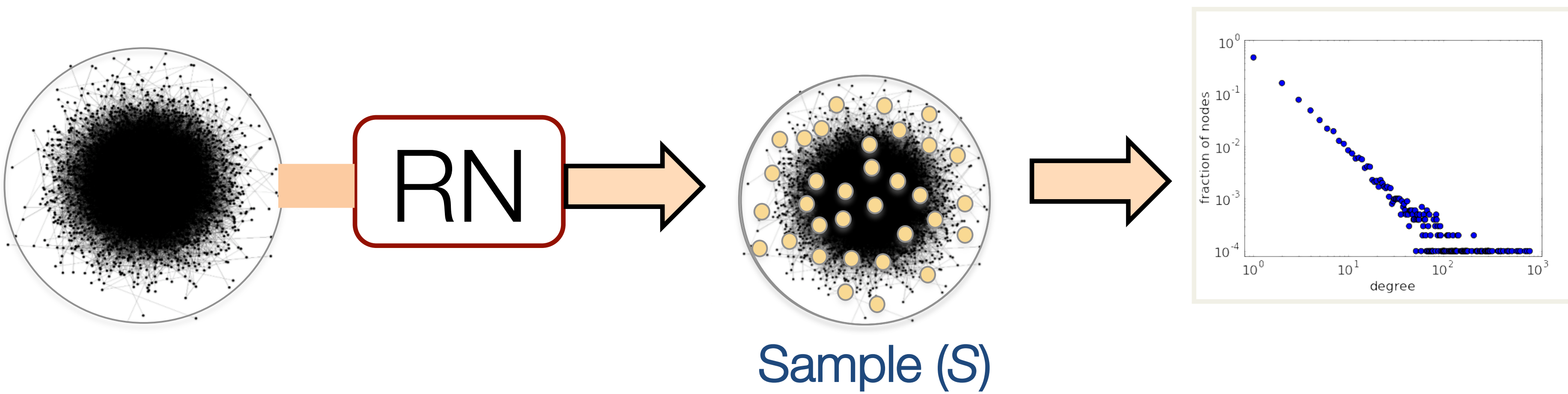
https://www.facebook.com/note.php?note_id=469716398919

Sampling methods
Task 1, Full Access assumption

- Uniform node sampling
  - Random node selection (RN)
- Non-uniform node sampling
  - Random degree node sampling (RDN)
  - Random pagerank node sampling (RPN)
- Uniform edge sampling
  - Random Edge selection (RE)
- Non-uniform edge sampling
  - Random node-edge (RNE)

Random Node Selection (RN)

- In this strategy, a node is selected uniformly and independently from the set of all nodes
  - The sampling task is trivial if the network is fully accessible.
- It provides unbiased estimates for any nodal attributes:
  - Average degree and degree distribution
  - Average of any nodal attribute
  - *f(u)* where *f* is a function that is defined over the node attributes



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Random Degree node selection (RDN)

- In this sampling, selection of a node is proportional to its degree
  - If $\pi(u)$ is the probability of selecting a node, $\pi(u) = \frac{d(u)}{2m}$
  - Node can be sampled using inverse-transform method, For π , we simply need to construct its cmf, say Π , then the sampled node, *x* is obtained by, $x = \Pi^{-1}(U), \text{where}, U \sim Uni(0,1)$
  - A second method is to first choose one edge uniformly, then choose one of its end-point with equal probability, clearly,

$$\pi(x) = \sum_{e \in inc(x)} \frac{1}{2m} = \frac{d(u)}{2m}$$

- High degree nodes have higher chances to be selected
  - Average degree estimation is higher than actual, and degree distribution is biased towards high-degree nodes.
  - Any nodal estimate is biased towards high-degree nodes.

Random pagerank node sampling (RPN) [Leskovec '06]

- Pagerank in the stationary distribution vector of a specially constructed Markov process
  - Visit a neighbor following an outgoing link with probability *c* (typically kept at 0.85), and jump to a random node (uniformly) with probability *1-c*
  - Pagerank vector satisfies following eigenvector equations: $\pi = \left(cA^T D^{-1} + (1-c)U\right)\pi = M\pi$ where π is the eigenvector of *M* with the eigenvalue 1
  - Pagerank can be computed efficiently by power method
- Node *u* is sampled with a probability which is proportional to $c \cdot \frac{d_{in}(u)}{m} + \frac{1-c}{n}$
  - When *c=1*, the sampling is similar to RDN for the directed graph,
  - When *c=0* the sampling is similar to RN
- Nodes with high in-degree have higher chances to be selected
  - Due to the uniform random jump, high degree bias of RDN is somewhat reduced. So, it provides better estimation accuracy than RDN for average degree and degree distribution.

Random Edge Selection (RE)

- In a random edge selection, we uniformly select a set of edges and the sampled network is assumed to comprise of those edges.
- A vertex is selected in proportion to its degree
  - If $\rho = \frac{|E_S|}{|E|}$, the probability of a vertex *u* to be selected is: $1-(1-\rho)^{d(u)}$
  - when $\rho \to 0$ the probability is: $\rho \cdot d(u)$
  - With more sample degree bias is reduced
  - The selection of vertices are not independent as both endpoints of an edge are selected
- Nodal statistics will be biased to high-degree vertices
- Edge statistics is unbiased due to the uniform edge selection.

Estimate node/edge properties in original network

Sample representative subgraph/subnetwork

Estimate frequency of subgraph patterns

Data Access Assumption	Task 1	Task 2	Task 3
Full Access	✓		
Restricted Access	✓		
Data Stream Access			

Sampling Objective

Sampling methodology

Public Facebook data can only be accessed by generating user IDs and crawling

http://www.wired.com/wiredscience/2012/04/facebook-disease-friends/

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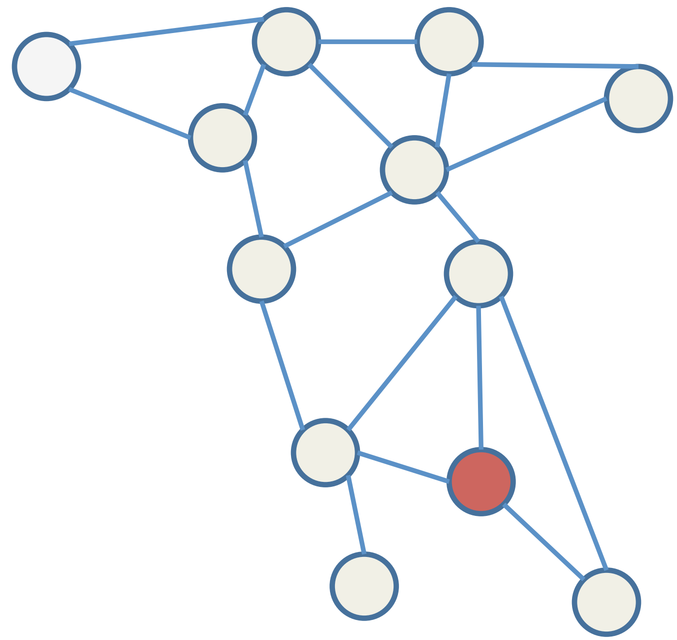
Sampling under restricted (or full) access Assumption

- Assumptions
  - The network is connected, (if not) we can ignore the isolated nodes
  - The network is hidden, however it supports crawling, i.e. it allows to explore the neighbors of a given node. Access to one seed node or a collection of seed nodes is given.
- Methods
  - Graph traversal techniques (exploration without replacement)
    - Breadth-First Search (BFS)
    - Depth-First Search (DFS)
    - Forest Fire (FF)
    - Snowball Sampling (SBS)
  - Random walk techniques (exploration with replacement)
    - Classic Random Walk
    - Markov Chain Monte Carlo (MCMC) using Metropolis-Hastings algorithm
    - Random walk with restart (RWR)
    - Random walk with random jump (RWJ)
- During the traversal or walk, the visited nodes are collected in a sample set and those are used for estimating network parameters

Breadth-first Sampling

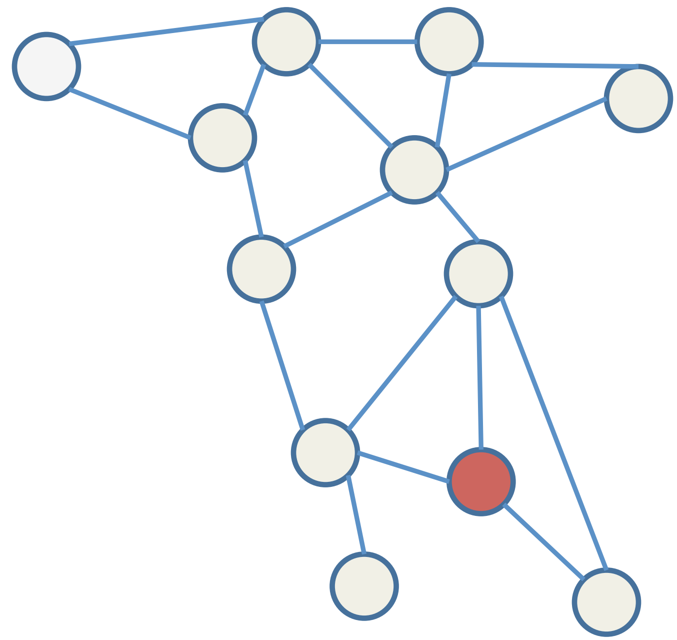
- At each iteration, earliest discovered but not yet visited node is selected
- For a selected node, the node is visited and all its neighbors are discovered
- It samples nodes from a specific region of the network
- It discovers all nodes within some distance from the seed node
- Nodal statistics are taken over the selected nodes.
- This sampling is biased as high-degree nodes have higher change to be sampled
- Nodal estimations are biased towards nodes with higher degree.



- A variation of this is depth first sampling which uses depth-first walk instead of breadth-fast
- Similar to BFS sampling, nodal estimates are biased towards high degree nodes

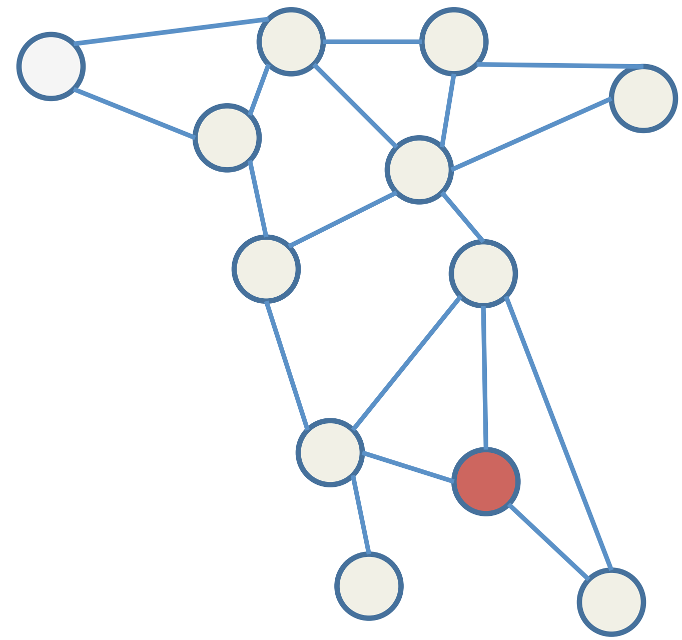
Depth-first Sampling

- At each iteration, we select the latest explored but, not-yet-visited node
- DFS explores first the nodes that are faraway from the seed
- The sampling is biased as high degree nodes has higher chance to be selected
- Same as BFS walk, estimation is biased towards nodes with higher degree.



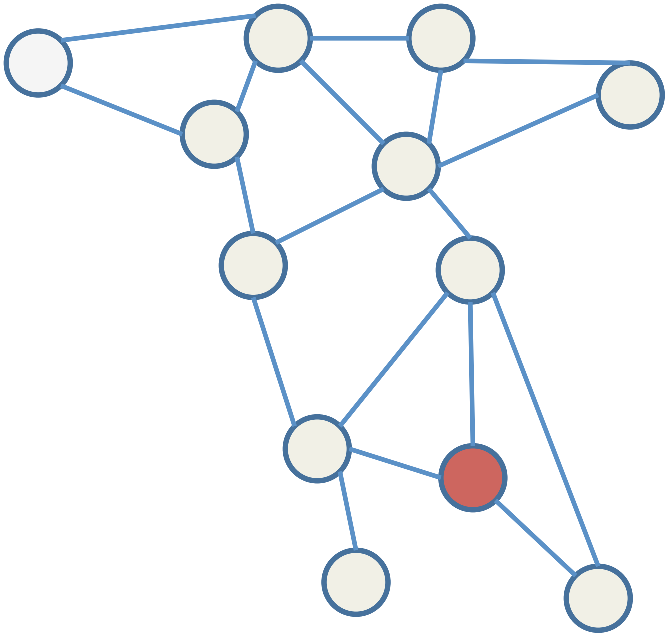
Forest Fire (FF) Sampling [Leskovec '06]

- FF is a randomized version of BFS
- Every neighbor of current node is visited with a probability *p.* For *p=1* FF becomes BFS.
- FF has a chance to die before it covers all nodes.
- It is inspired by a graph evolution model and is used as a graph sampling technique
- its performance is similar as BFS sampling



Snowball Sampling

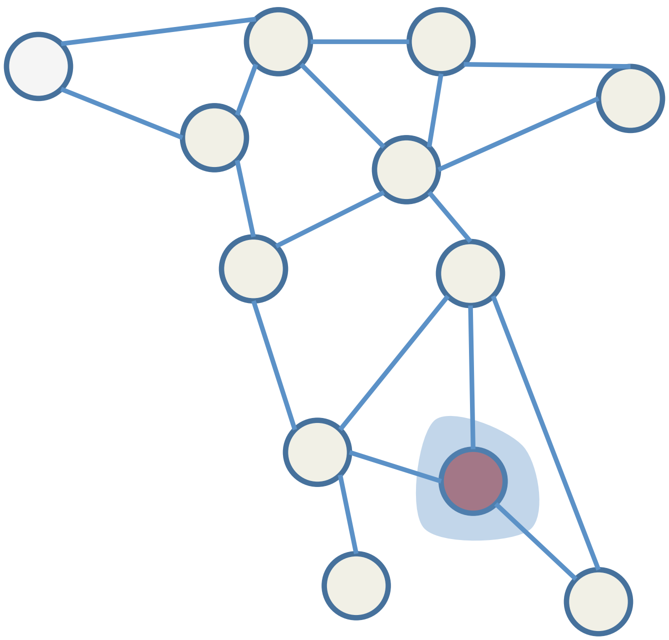
- Similar to BFS
- *n*-name snowball sampling is similar to BFS
- at every node *v*, not all of its neighbors but exactly *n* neighbors are chosen randomly to be scheduled
- A neighbor is chosen only if it has not been visited before.
- Performance of snowball sampling is also similar to BFS sampling



Snowball: n=2

Classic Random Walk Sampling (RWS)

- At each iteration, one of the neighbors of currently visiting node is selected to visit
- For a selected node, the node and all its neighbors are discovered
- The sampling follows depth-first search pattern



$$p_{u,v} = \begin{cases} 1/d(u) & \text{if } v \in adj(u) \\ 0 & \text{otherwise} \end{cases}$$

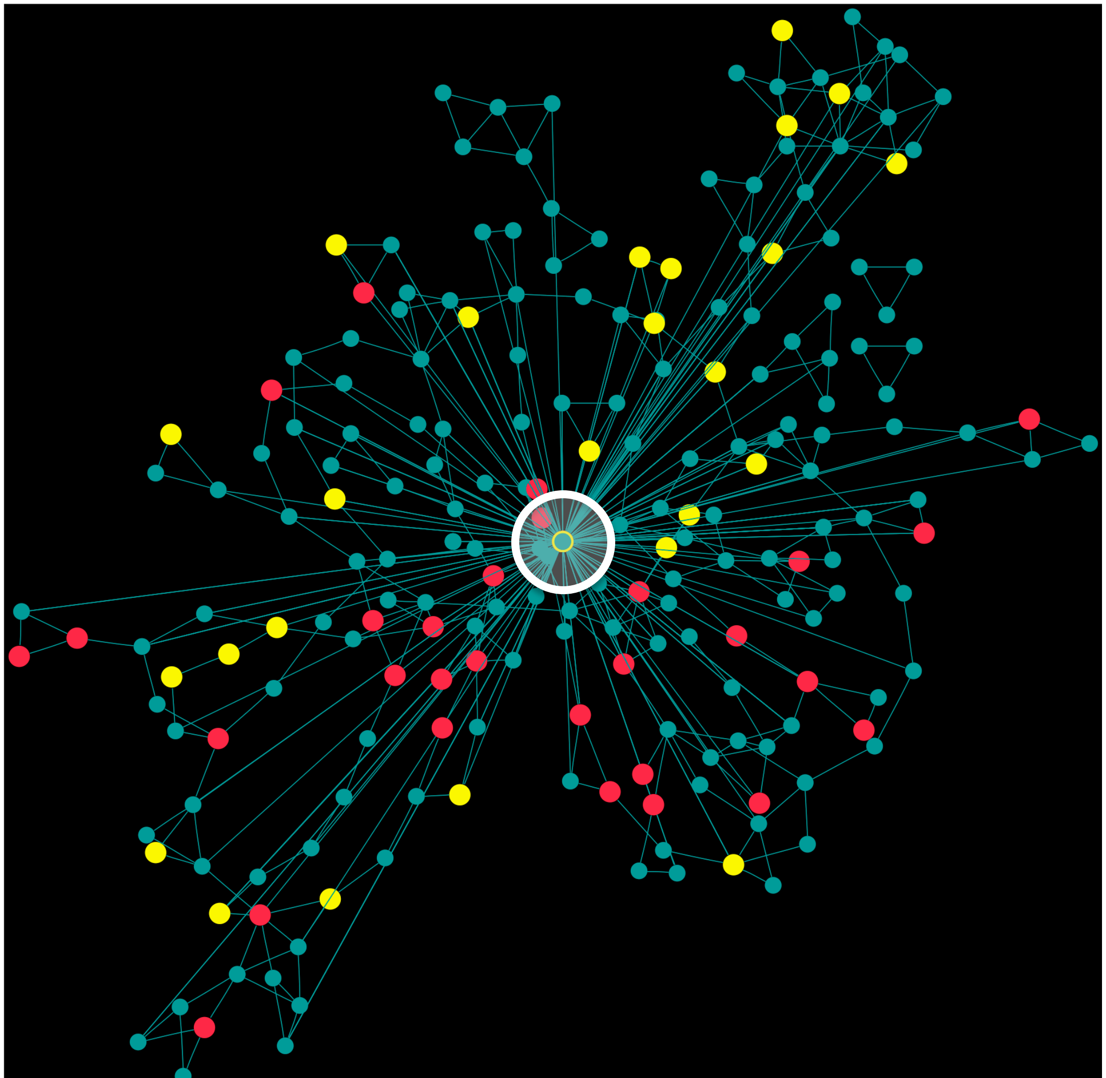
- This sampling is biased as high-degree nodes have higher change to be sampled, probability that node u is sampled is

$$\pi(u) = \frac{d(u)}{2m}$$

Other variants of random walk

- Random walk with restart (RWR)
  - Behaves like RWS, but with some probability *(1-c)* the walk restarts from a fixed node, *w*
  - The sampling distribution over the nodes models a non-trivial distance function from the fixed node, *w*
- Random walk with random jump (RWJ)
  - Access to arbitrary node is required
  - RWJ is motivated from the desire of simulating RWS on a directed network, as on directed network RWS can get stuck in a sink node, and thus no stationary distribution can be achieved
  - Behaves like RWS, but with some probability *(1-c)*, the walk jumps to an arbitrary node with uniform probability.
  - The stationary distribution is proportional to the pagerank score of a node, so the analysis is similar to RPN sampling

Exploration based sampling will be biased toward high degree nodes



How can we modify the algorithms to ensure nodes are sampled uniformly at random?

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Uniform sampling by exploration

- Traversal/Walk based sampling are biased towards high-degree nodes
- Can we perform random walk over the nodes while ensuring that we sample each node uniformly?
- Challenges
  - We have no knowledge about the sample space
  - At any state, only the currently visiting nodes and its neighbors are accessible
- Solution
  - Use random walk with the Metropolis-Hastings correction to accept or reject a proposed move
  - This can guaranty uniform sampling (with replacement) over all the nodes

Metropolis-Hastings (MH) algorithm

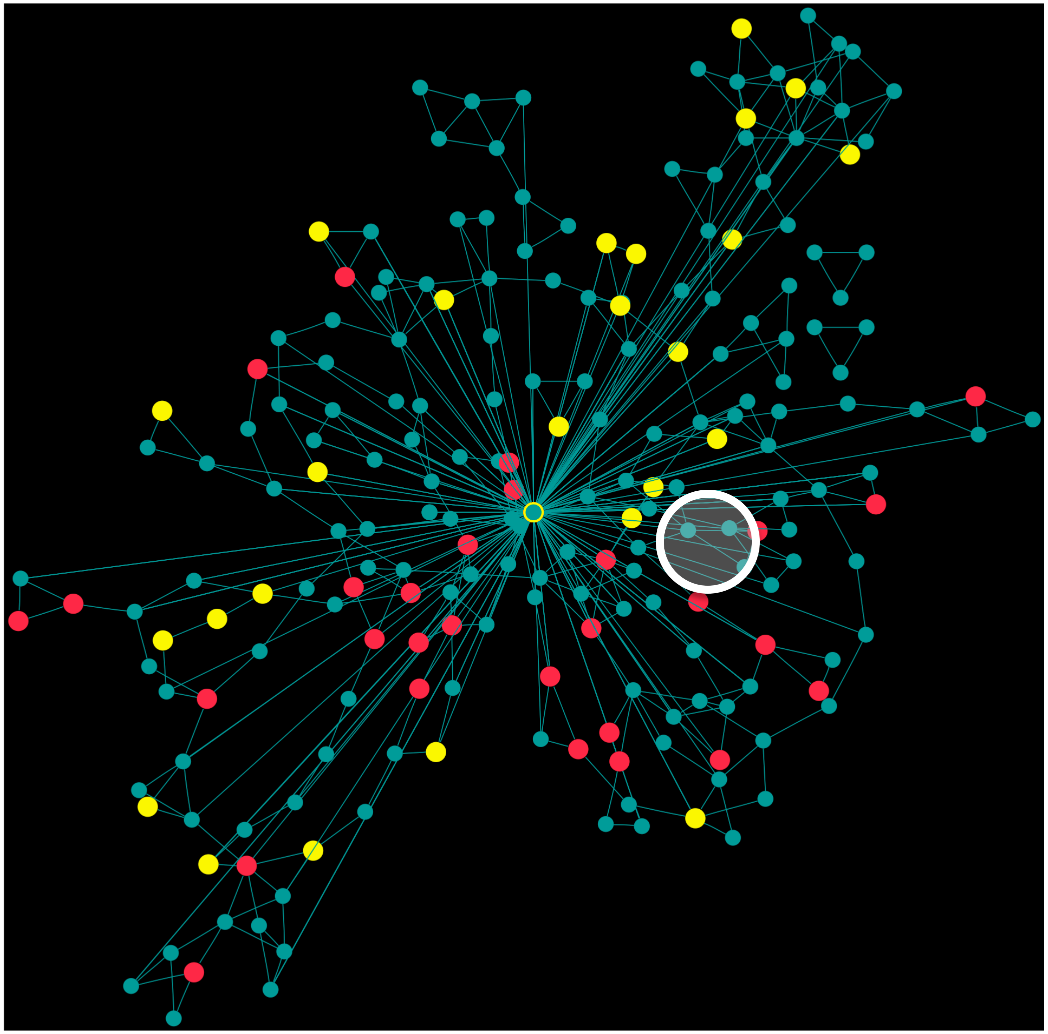
- Problem: Assume that we want to generate a random variable V taking values $V=\{1, 2, \cdots, n\}$, according to a target distribution $\{\pi_i\}$, $i \in V$ (the vertices of the given network)
  - $\pi_i = b_i / C$, all b_i are strictly positive, n is large, and normalizing constant $C=\sum_{i=1}^{n} b_i$ is hard to compute

- Solution: Simulate a Markov chain such that stationary distribution of the chain coincides with the target distribution
  - Construct a Markov chain $\{X_t, t=0, 1, \cdots\}$ on M using an arbitrary transition probability matrix, $\mathbf{Q}=(q_{ij})$ ($\mathbf{Q}$ is also called the proposal distribution)
  - If $X_t = i$, generate Y such that $P(Y=j)=q_{ij}$, $i,j \in V$
  - Now, $X_{t+1} = \begin{cases} j & \text{with probability, } \alpha_{ij} = \min\{ b_j q_{ji} / b_i q_{ij}, 1\} \\ i & \text{with probability } 1-\alpha_{ij} \end{cases}$
  - The stationary distribution of the above Markov chain is $\pi=\{\pi_i\}$

Uniform node sampling with Metropolis-Hastings method [Henzinger '00]

- It works like random walk sampling (RWS), but it applies a correction so that high-degree bias of RWS is eliminated systematically
  - The proposal distribution, $\mathbf{Q}$ chooses one of the neighbor (say, j) of the current node (say, i) uniformly, thus proposal distribution works as RWS, $q_{ij} = 1/d(i)$
- Now, $X_{t+1} = \begin{cases} j & \text{with probability, } \alpha_{ij} = \min\left\{\frac{b_j q_{ji}}{b_i q_{ij}}, 1\right\} \\ i & \text{with probability } 1 - \alpha_{ij} \end{cases}$
  - For uniform target $b_i = b_j$, for RWS like proposal distribution, $q_{ij} = 1/d_i$ and $q_j = 1/d_j$
  - Thus, $\alpha_{ij} = \min\{d_i/d_j, 1\}$ if $d(j) \leq d(i)$, the choice is accepted only with probability 1, otherwise with probability $d(i)/d(j)$
- If a graph have n vertices, using the above MH variant, every node is sampled with $1/n$ probability

When sampling algorithm selects nodes non-uniformly…



Can we remove the sampling bias in nodal statistics by post-processing?

Correction of arbitrary nodal attributes for biased sampling (cont.)

- Assume, $\{x_s\}_{\{s=1\}}^{t}$ are the nodes sampled to compute the unbiased expectation of nodal attribute, f which is $E_u[f]$
- π is a distribution that we achieve by a biased sampling
- Let's define a weight function $w: V \rightarrow R$ such that $w(x_i) = 1/\pi(x_i)$
- Then, $E_u[f] = \frac{1/t \sum_{s=1}^{t} w(x_s)\cdot f(x_s)}{1/t \sum_{s=1}^{t} w(x_s)} = \frac{\sum_{s=1}^{t} w(x_s)\cdot f(x_s)}{\sum_{s=1}^{t} w(x_s)}$

Example (Kurant

- Estimating average degree by SRW, here $\pi(x_s) = 1/d_{x_s}$,
- Unbiased estimate of average degree is,

$$E_u(\bar{d}) = \frac{\sum_{s\in[1..t]} (1/d_{x_s})(d_{x_s})}{\sum_{s\in[1..t]} 1/d_{x_s}} = \frac{t}{\sum_{s\in[1..t]} 1/d_{x_s}}$$

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ANALYSIS

Task 1 performance summary over all the sampling method

Sampling	Direct sampling of Nodes or edges	Exploration (walk or traversal)
Uniform node sampling	RN	MH (uniform target distribution)
Almost Uniform node sampling	RNE	
Exactly Degree proportional	RDN	RWS
Apparently degree proportional (when sample size is small)	RE	BFS, FF, Snowball
PageRank proportional Sampling	RPN	RWJ

Comparison

- Node property estimation
  - Uniform node selection (RN) is the best as it selects each node uniformly
  - Average degree and degree distribution is unbiased
- Edge property estimation
  - Uniform edge selection (RE) is the best as it select each edge uniformly
  - For example, we can obtain an unbiased estimate of assortativity by RE method

Method	**Vertex Selection Probability, $\pi(u)$** $\lvert V\rvert=n, \lvert E\rvert=m,$
RN, MH-uniform target	$1/n$
RDN, RWS	$d(u)/2m$
RPN, RWJ	$c\cdot d_{in}(u)/m+(1-c)\cdot 1/n$ (undirected) $c\cdot d(u)/2m+(1-c)\cdot 1/n$ (directed)
RE	$\sim d(u)/2m$
RNE	$1/n\ \left(1+\sum_{x\in adj(u)} 1/adj(x)\right)$

Expected average degree and degree distribution for walk based methods

- For a degree value k assume p_k is the fraction of vertices with that degree $\sum_{k>0} p_k = 1$

- **Uniform Sampling,** node sampling probability, $\pi(v) = \frac{1}{|V|} = \frac{1}{n}$
  - Expected value of p_k: $q_k = \sum_{v \in V} \pi(v) \cdot 1_{d(v)=k} == \frac{1}{|V|} \cdot p_k \cdot |V| = p_k$
  - Expected observed node degree: $\sum_{k>0} k \cdot q_k = \sum_{k>0} k \cdot p_k$

Overestimate high-degree vertices, underestimate low-degree vertices

- **Biased Sampling** (degree proportional), $\pi(v) = \frac{d(v)}{2 \cdot |E|} = \frac{d(v)}{2m}$
  - Expected value of p_k: $q_k = \sum_{v \in V} \pi(v) \cdot 1_{d(v)=k} == \frac{k}{2 \cdot |E|} \cdot p_k \cdot |V| = \frac{k \cdot p_k}{\bar{d}}$
  - Expected observed node degree: $\sum_{k>0} k \cdot q_k = \frac{\sum_{k>0} k^2 \cdot p_k}{\bar{d}} = \frac{\overline{d^2}}{\bar{d}}$

Overestimate average

Example

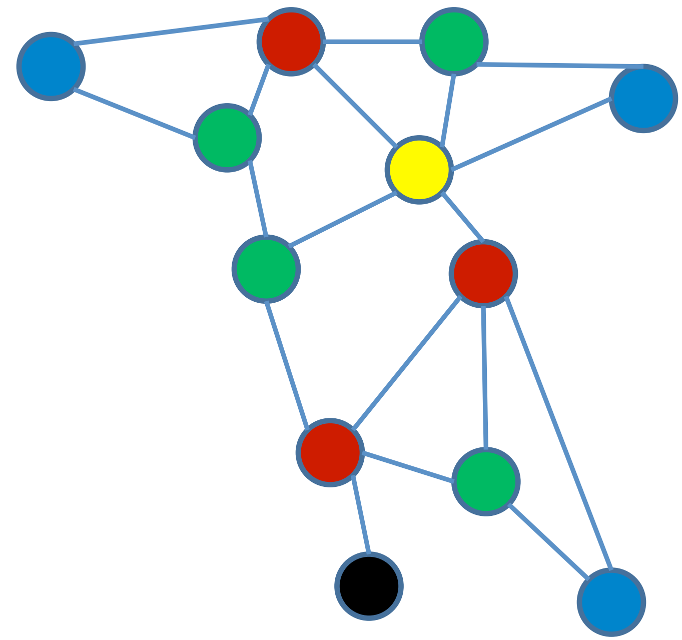
- Actual degree distribution

$$q_k = \left\{ \frac{1}{12}, \frac{3}{12}, \frac{4}{12}, \frac{3}{12}, \frac{1}{12} \right\}$$

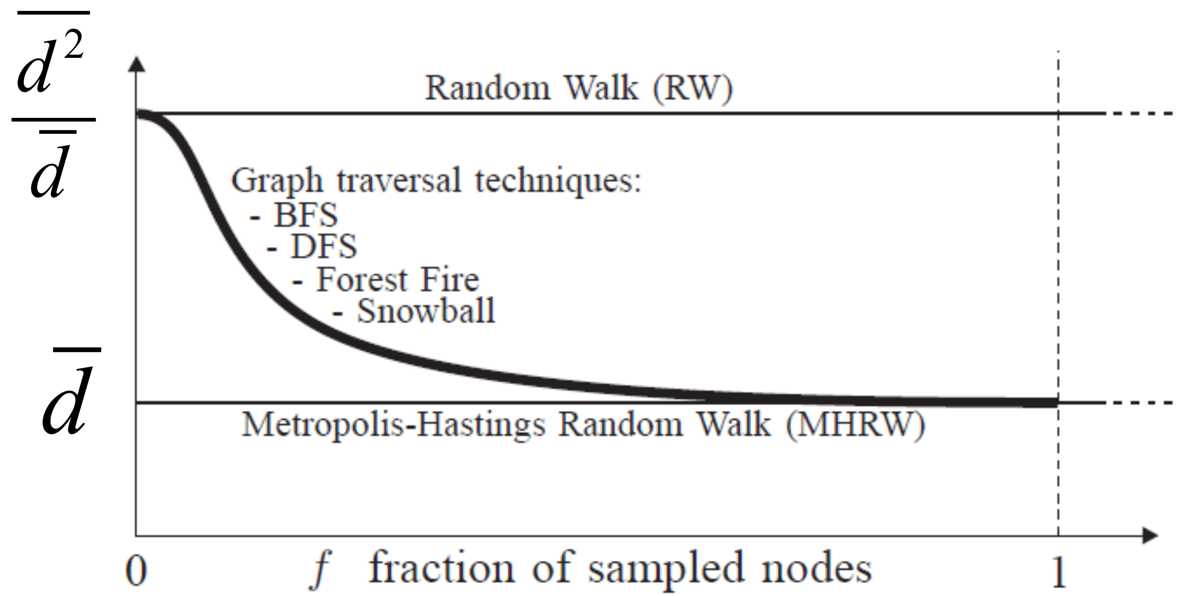
- Average degree = 3
- RWS degree distribution

$$q_k = \left\{ \frac{1}{36}, \frac{6}{36}, \frac{12}{36}, \frac{12}{36}, \frac{5}{36} \right\}$$

- RWS average degree
  - 3.39



Expected average degree for traversal based methods [Kurant '10]



- Note that, for walk based method, the sampling is with replacement, so their analysis does not chance with the fraction of sampling
- Traversal based method behaves like RWS when the sample size is small, but as the sample size is increases its estimation quickly converges towards the true estimation
- Behavior of all the traversal method is almost identical.

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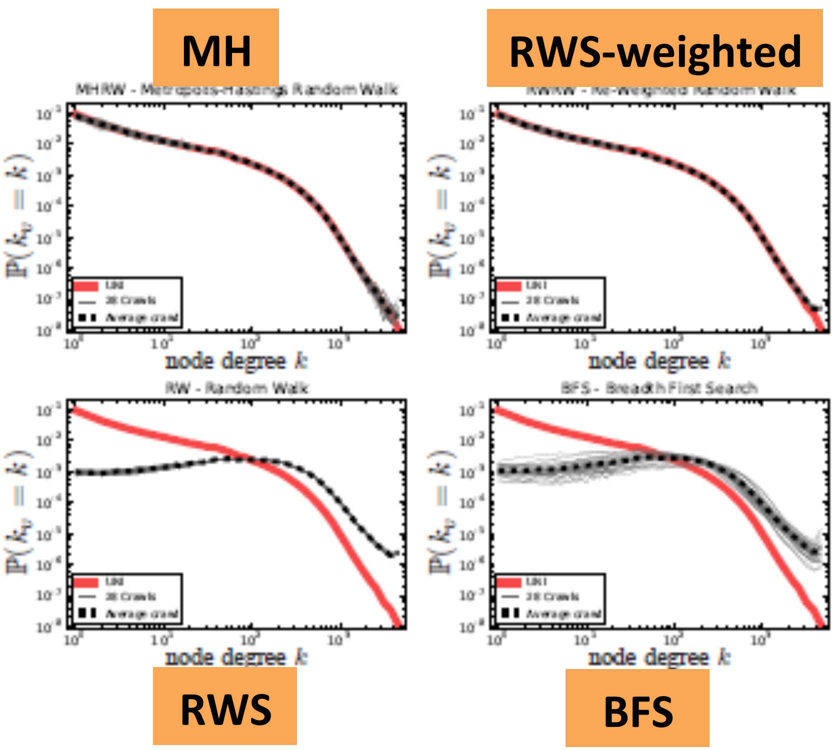
EMPIRICAL RESULTS

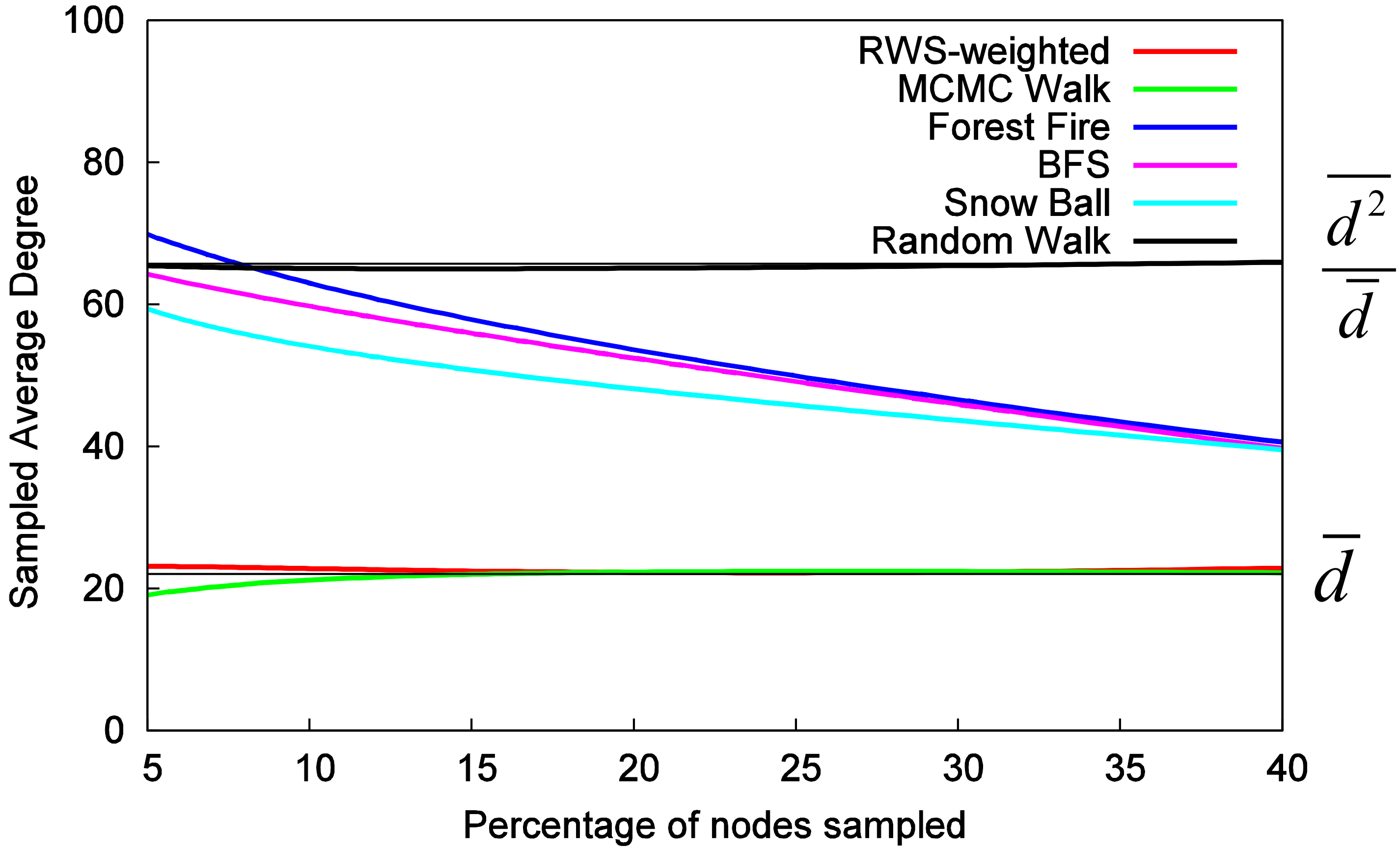
Comparison between different sampling strategies [Gjoka ’10, Gjoka ‘11]

- Gjoka et al. sampled Facebook network and compared the above sampling methods
- They confirmed that MH sampling and reweighted RWS can estimate degree distribution almost perfectly.



Average Degree Estimation	
BFS	285.9
RWS	338
MCMC	**95.2**
Actual	94.1
RWS (corrected)	93.9

Average degree estimation (astro-phy network)



Estimate node/edge properties in original network

Sample representative subgraph/subnetwork

Estimate frequency of subgraph patterns

Data Access Assumption

	Task 1	Task 2	Task 3
Full Access	✓		
Restricted Access	✓		
Data Stream Access	✓		

Sampling Objective

Sampling methodology

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Interaction networks can be extracted from dynamic communications

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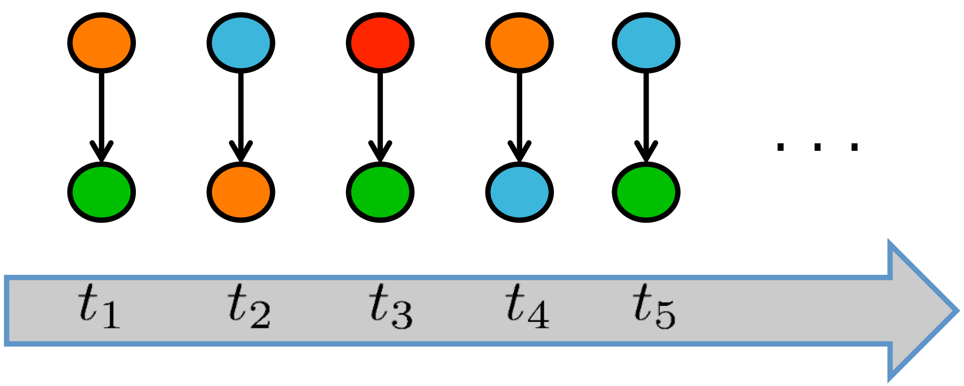
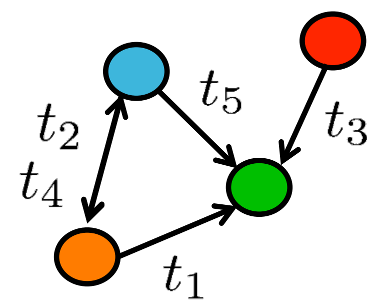
Sampling under data streaming access assumption

- Previous approaches assume:
  - Full access of the graph or Restricted access of the graph – access to only node's neighbors
- Data streaming access assumption:
  - A graph is accessed only sequentially as a stream of edges
  - Massive stream of edges that cannot fit in main memory
  - Efficient/Real-time processing is important



Stream of edges over time



Graph with timestamps

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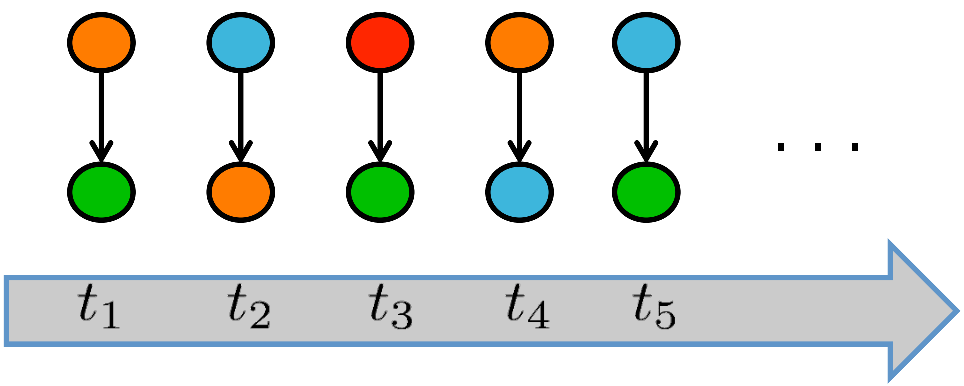
Sampling under data streaming access assumption

- The complexity of sampling under streaming access assumption defined by:
  - Number of sequential passes over the stream
  - Space required to store the intermediate state of the sampling algorithm and the output
    - Usually in the order of the output sample



Stream of edges over time

- *No. Passes*
- *Space*

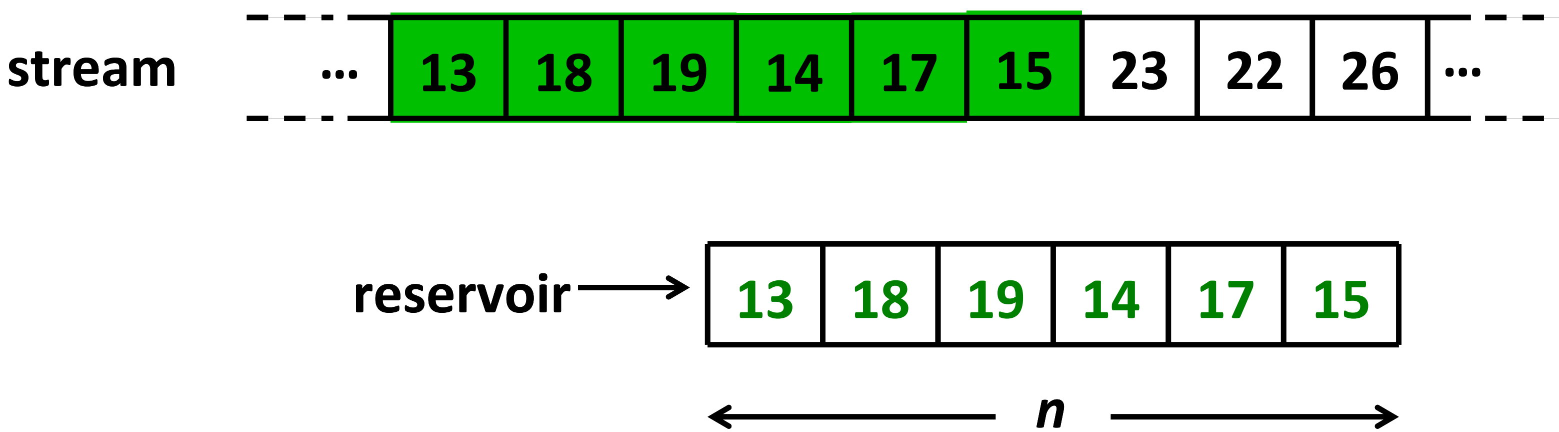
Sampling methods under data streaming access assumption

- Most stream sampling algorithms are based on *random reservoir sampling*

- Random Reservoir Sampling [Vitter'85]
  - A family of random algorithms for sampling from data streams
  - Choosing a set of *n* records from a large stream of *N* records
    - *n* << *N*
  - *N* is too large to fit in main memory and usually unknown
  - One pass, O(N) algorithm

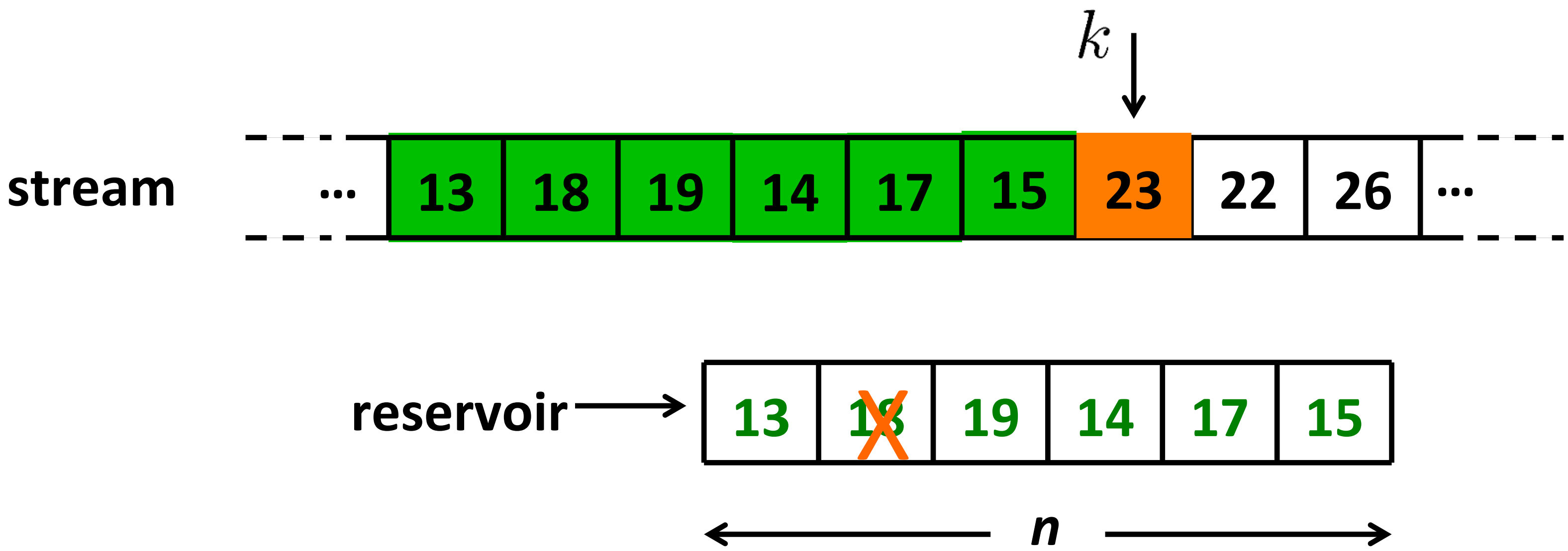
Reservoir Sampling Algorithm

Step 1: Add first *n* records to reservoir



Reservoir Sampling Algorithm

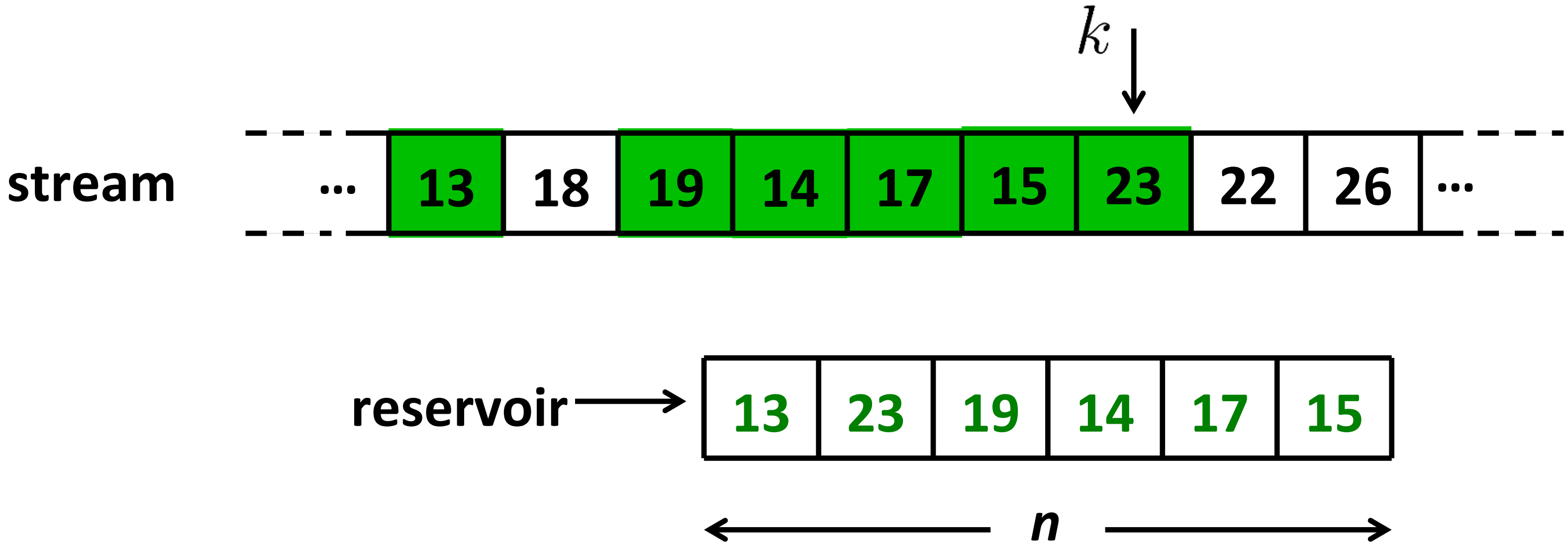
Step 2: Select the next record k with probability $P = n/k$



- When a record is chosen for the reservoir, it becomes a candidate and replaces one of the former candidates

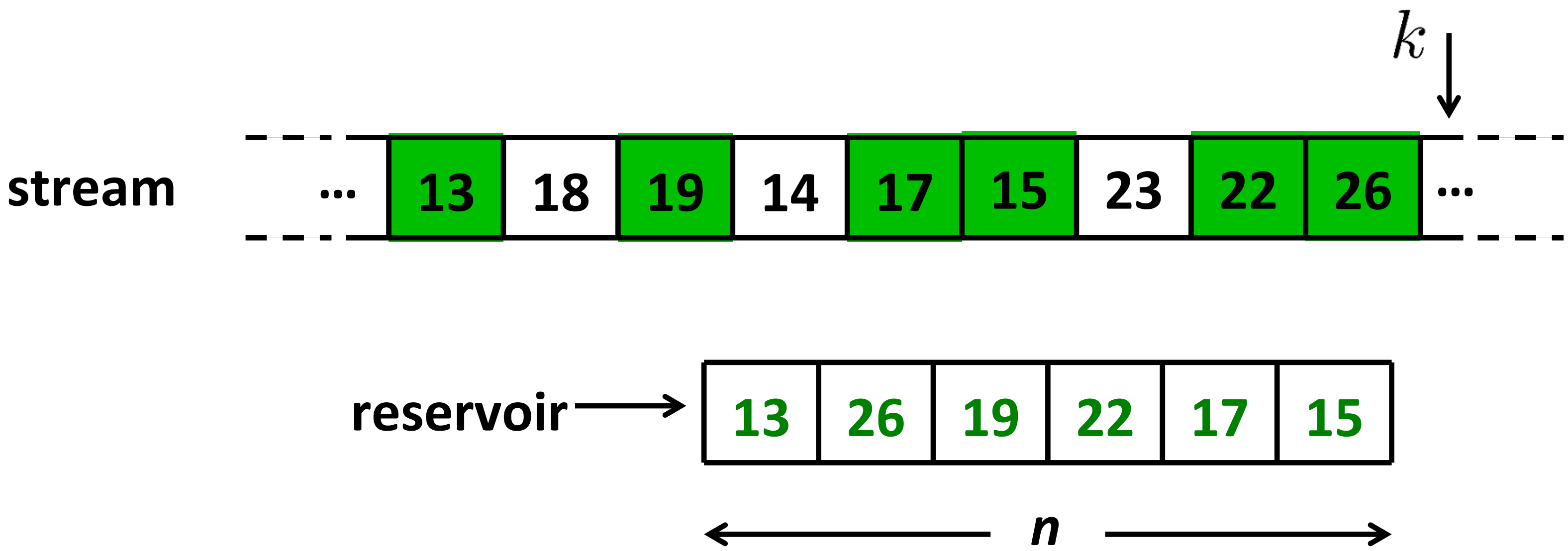
Reservoir Sampling Algorithm

Step 2: Select the next record k with probability $P = n/k$



Reservoir Sampling Algorithm

After repeating Step 2 …



- at the end of the sequential pass, the current set of *n* candidates is output as the final sample

Sampling methods under data streaming access assumption

- Streaming Uniform Edge Sampling
  - Extends traditional random edge sampling (RE) to streaming access

- Streaming Uniform Node Sampling
  - Extends traditional random node sampling (RN) to streaming access

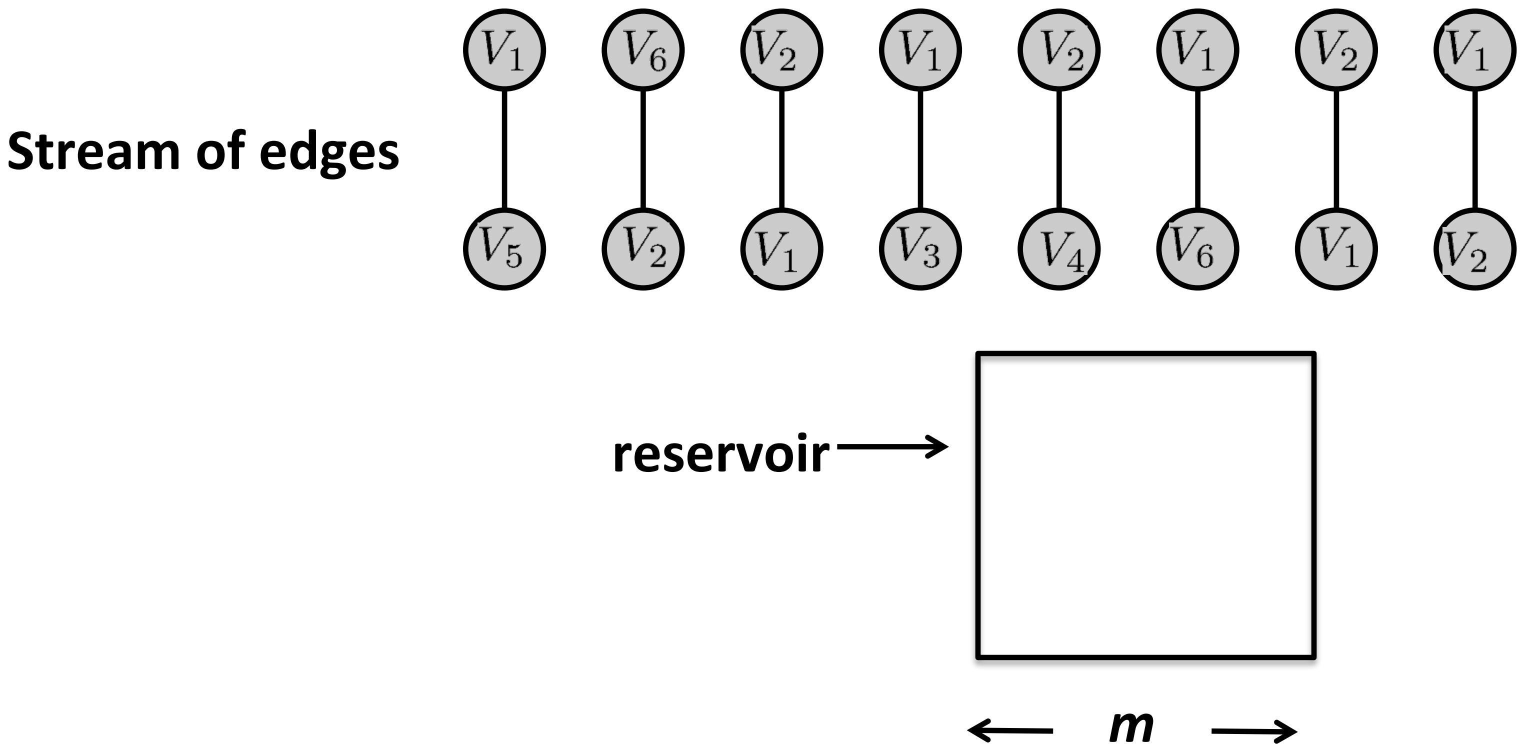
Sampling methods under data streaming access assumption

- Streaming Uniform Edge Sampling
  - Extends traditional random edge sampling (RE) to streaming access

- Streaming Uniform Node Sampling
  - Extends traditional random node sampling (RN) to streaming access

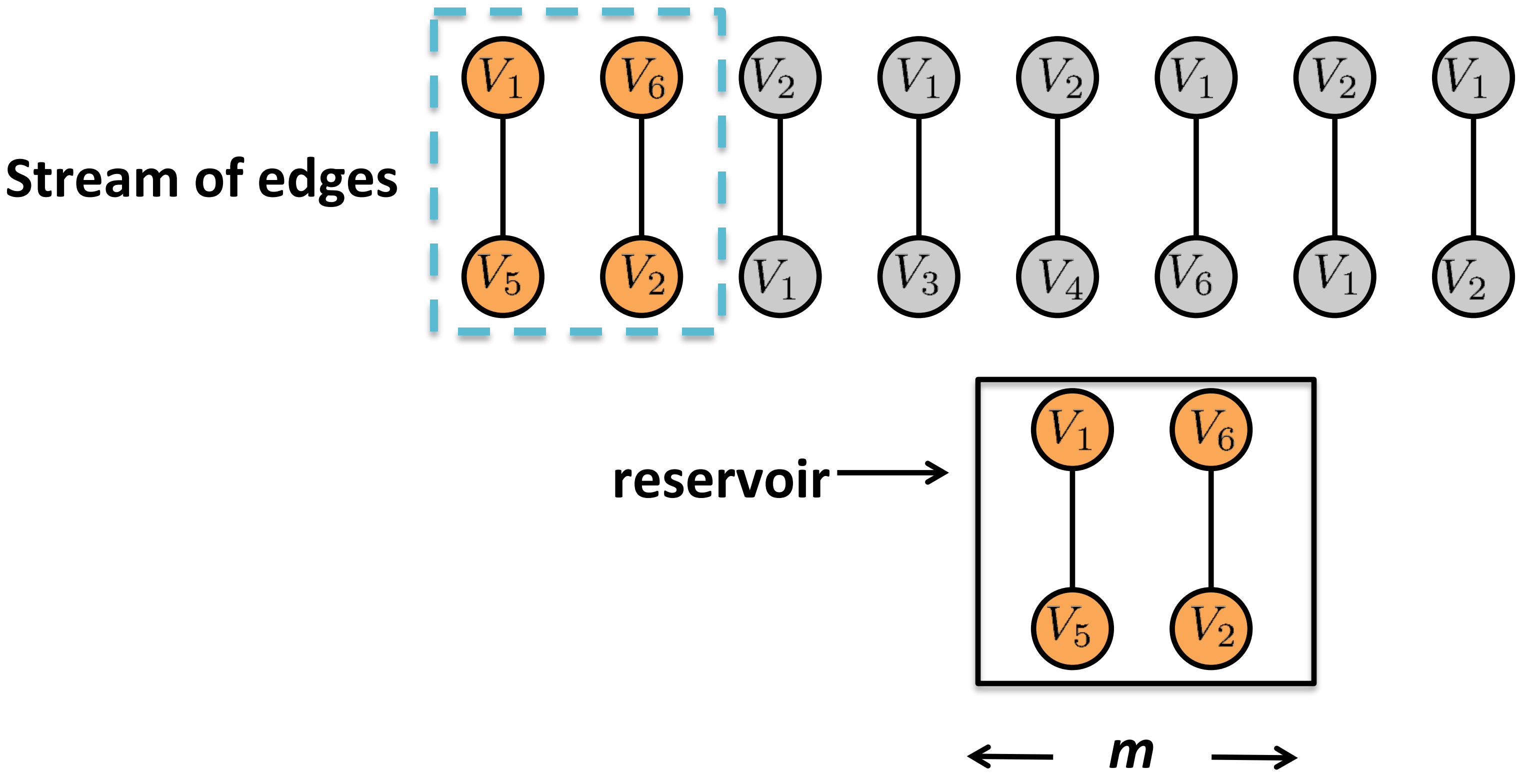
Streaming Edge Sampling (RE)

Step 0: Start with an empty reservoir of size m = 2



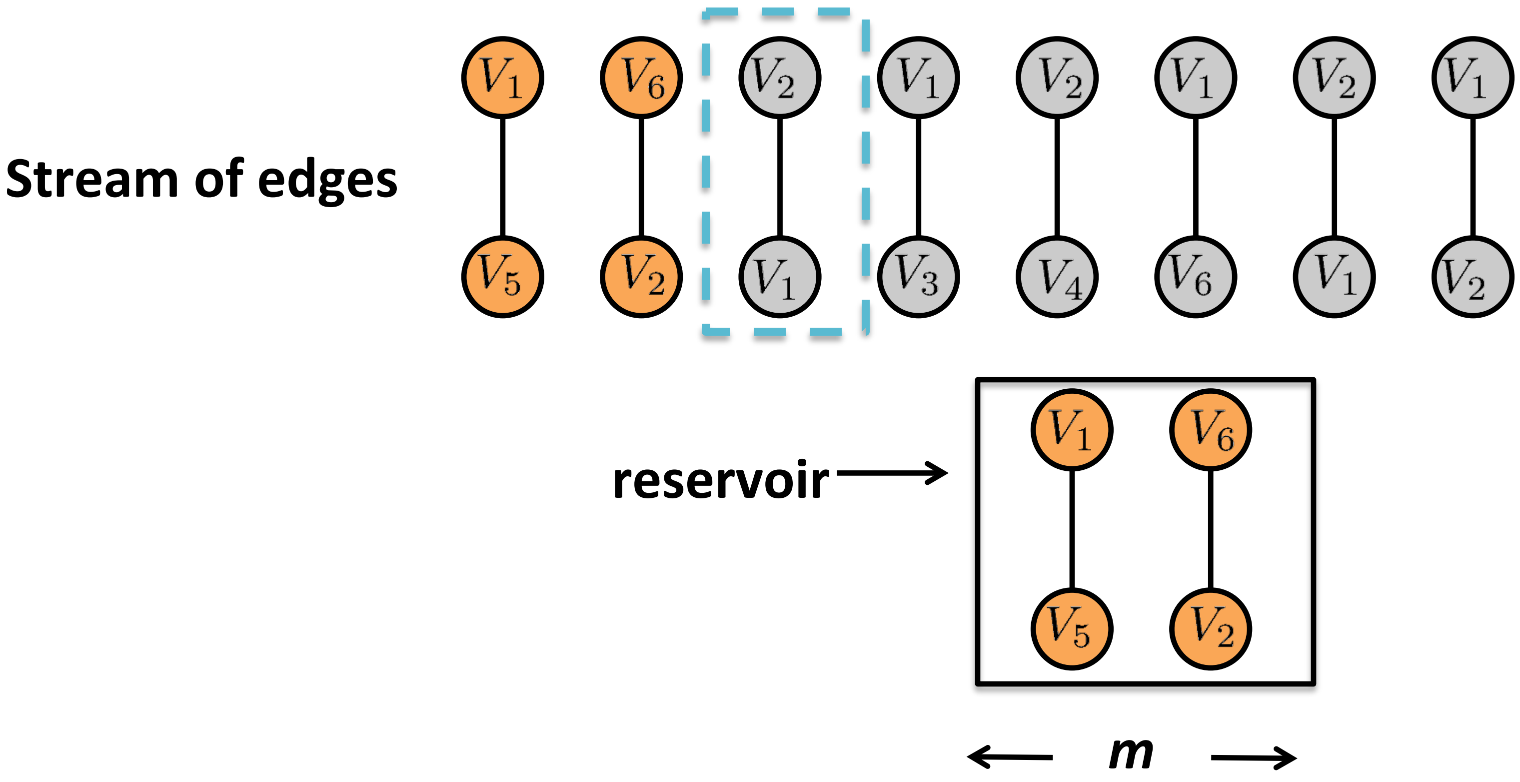
Streaming Edge Sampling (RE)

Step 1: Add first *m* edges to reservoir



Streaming Edge Sampling (RE)

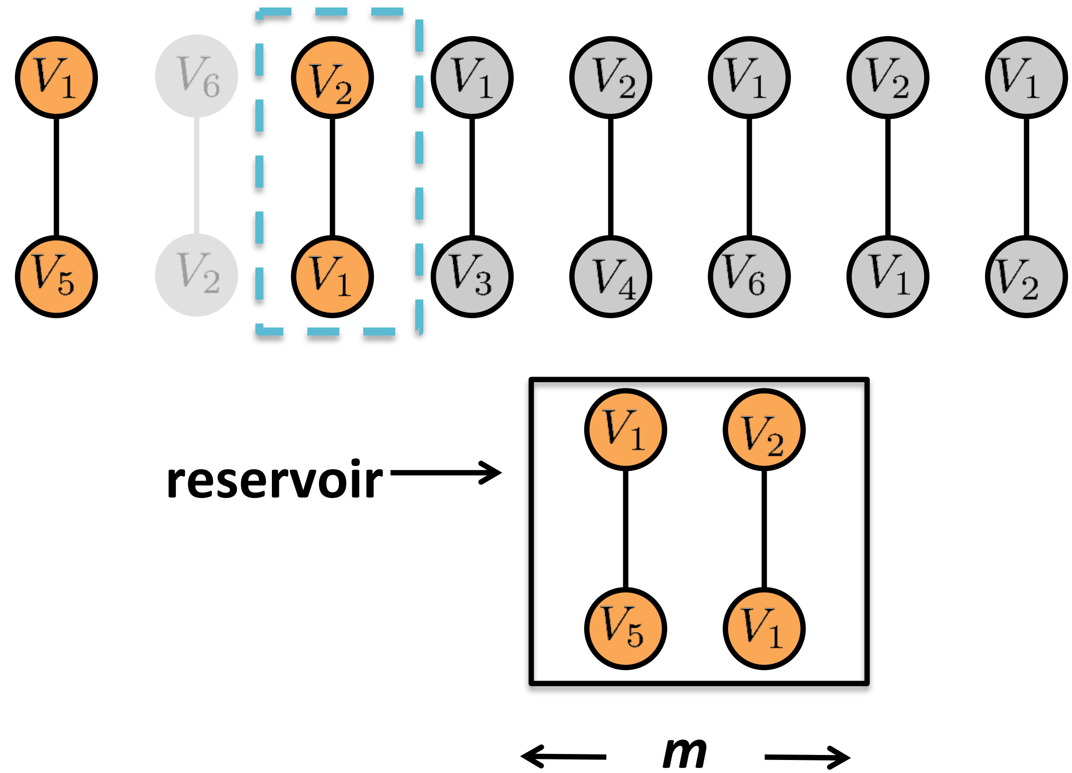
Step 2: Sample next edge V_2–V_1 **with prob.** $P = n/k$



Streaming Edge Sampling (RE)

Edge V_2–V_1 is selected

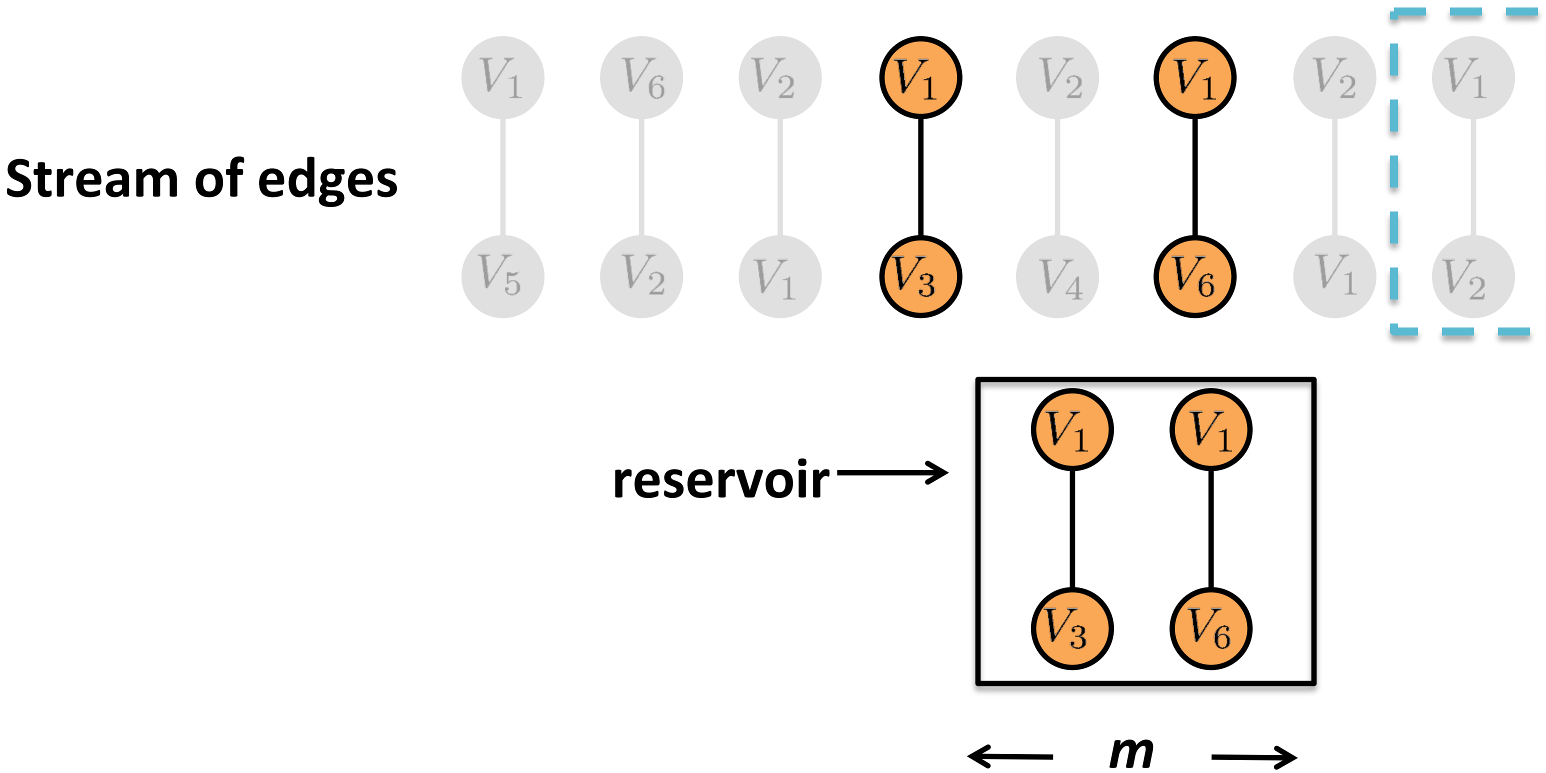
Stream of edges



$V_2 - V_1$ is selected replacing $V_6 - V_2$

Streaming Edge Sampling (RE)

At the end of the sequential pass . . .



- at the end of the sequential pass, the current set of *m edges* is output as the final sample

Min-Wise Sampling briefly …

- A random "tag" drawn independently from the Uniform(0, 1) distribution
- This "tag" is called the "hash value" associated with each arriving item
- The sample consists of the items with the *n* smallest tags/hash values seen thus far
- Uniformity follows by symmetry: every size-n subset of the stream has the same chance of having the smallest hash values

$$\boxed{\begin{array}{l}\text{For any arriving item } i \\ h(i) \sim Uniform(0,1)\end{array}}$$

Sampling methods under data streaming access assumption

- Streaming Uniform Edge Sampling
  - Extends traditional random edge sampling (RE) to streaming access
- Streaming Uniform Node Sampling
  - Extends traditional random node sampling (RN) to streaming access

Sampling from the stream directly *selects nodes proportional to their degree*

Not suitable for sampling nodes *uniformly*

Use Min-Wise Sampling

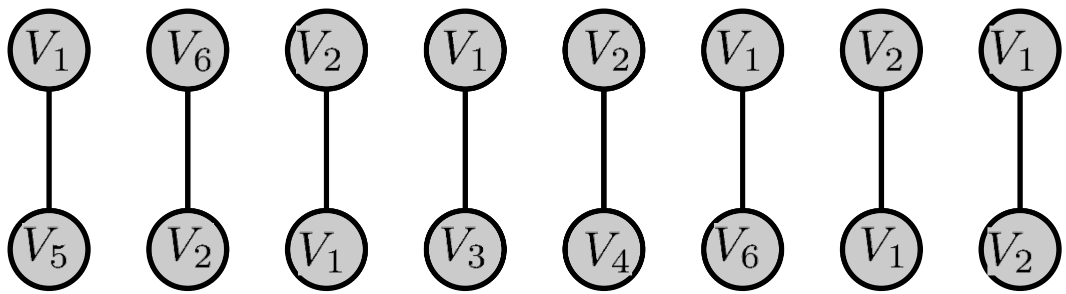
Streaming Uniform Node Sampling (RN)

- Assumption: nodes arrive into the system only when an edge that contains the new node is streaming into the system
- It is difficult to identify which *n* nodes to select a priori with uniform probability
- Use min-wise sampling
- Maintain a reservoir of nodes with top-n minimum hash values
- a node with smaller hash value may arrive late in the stream and replace a node that was sampled earlier

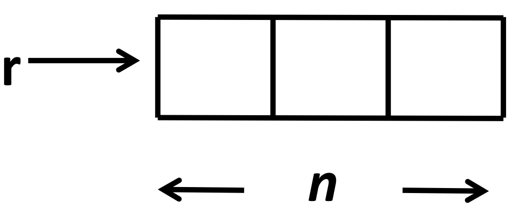
Streaming Uniform Node Sampling (RN) – Example

Step 0: Start with an empty reservoir

Stream of edges

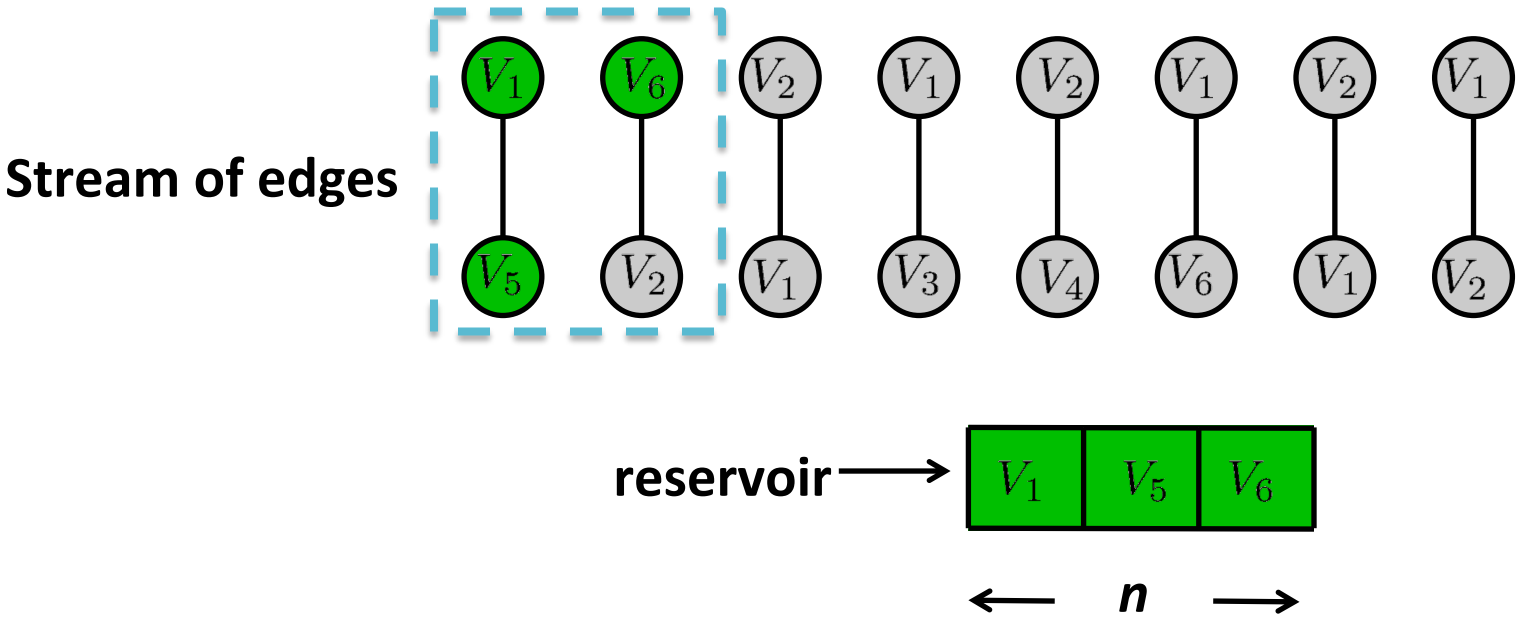


reservoir



Streaming Uniform Node Sampling (RN) – Example

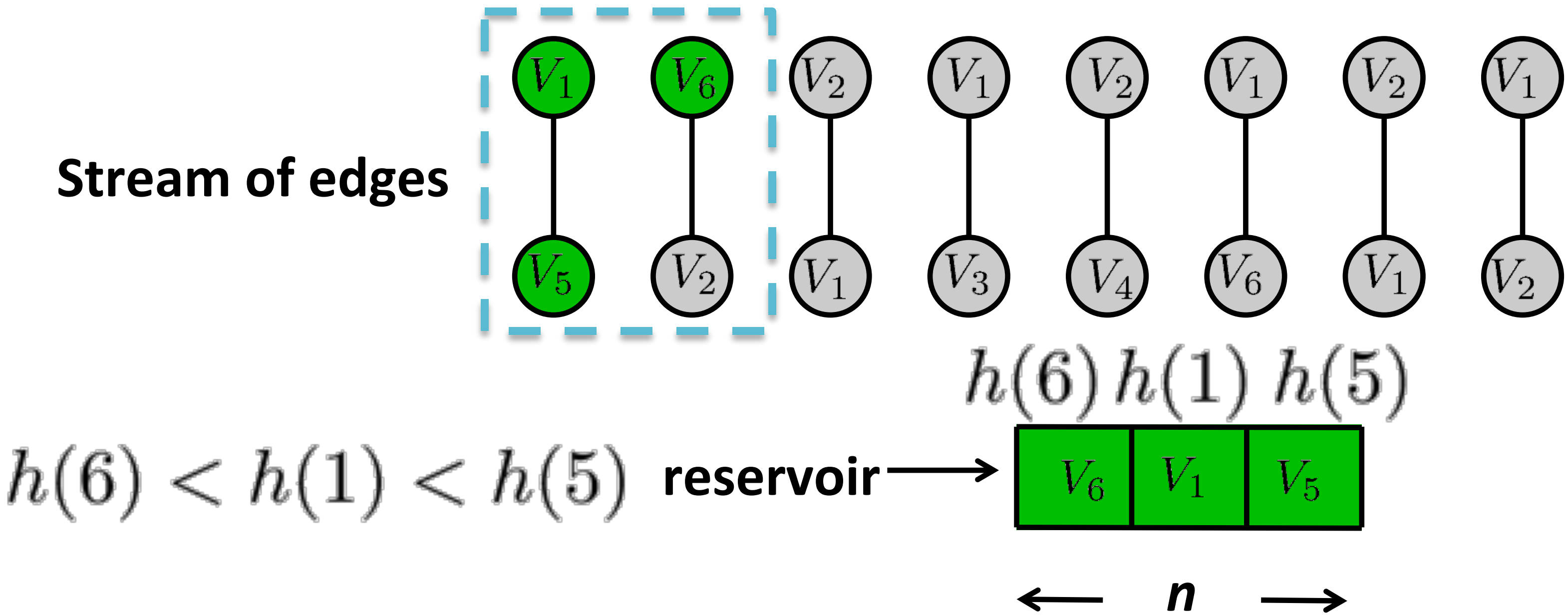
Step 1: Add first *n* nodes to reservoir



- Apply a uniform random Hash Function to the node id $h(i)$
- h defines a true random permutation on the node id's

Streaming Uniform Node Sampling (RN) – Example

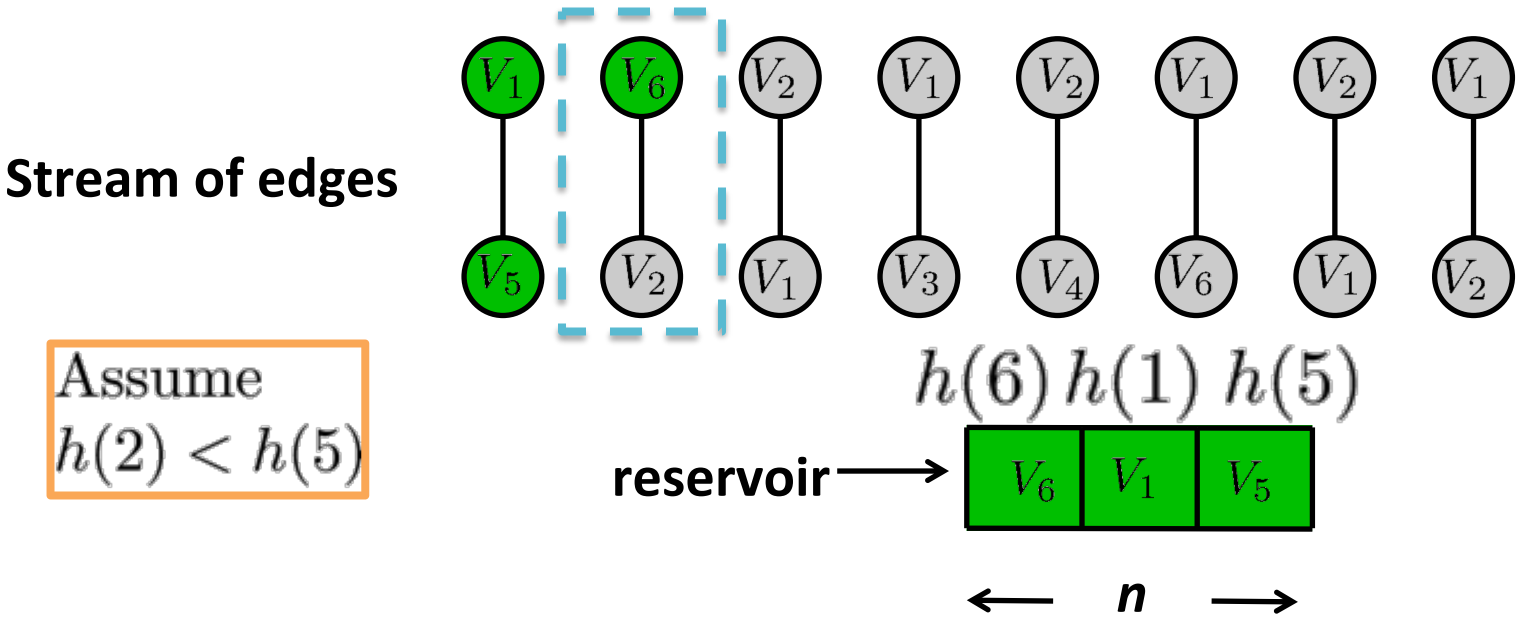
Step 1: Add first *n* nodes to reservoir



- Apply a uniform random Hash Function to the node id $h(i)$
- h defines a true random permutation on the node id's

Streaming Uniform Node Sampling (RN) – Example

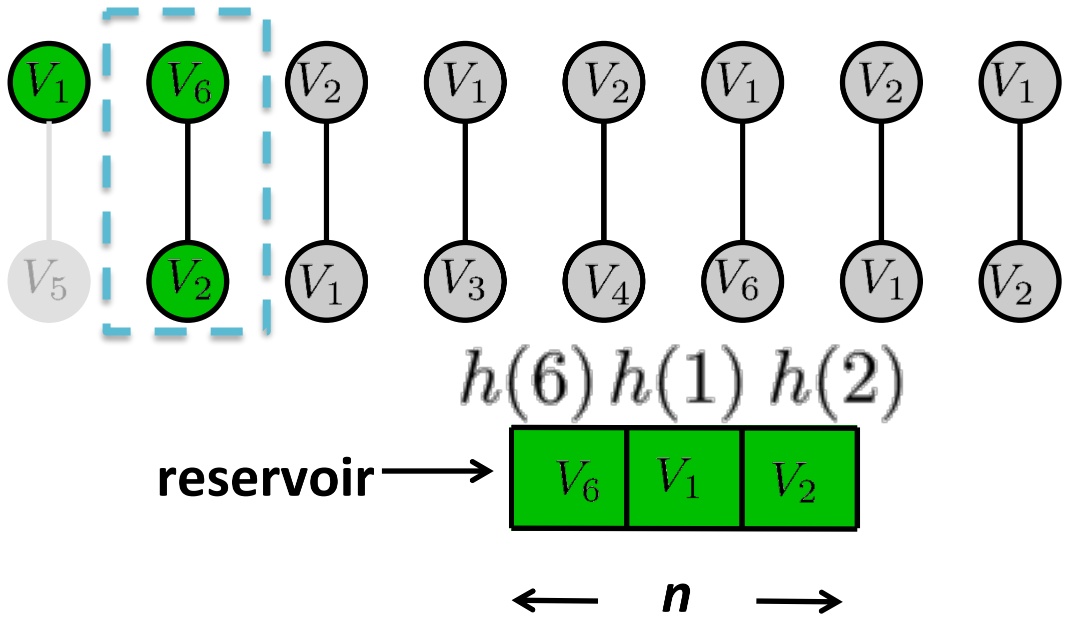
Step 2: Sample the next node . . . V_2



Streaming Uniform Node Sampling (RN) – Example

Step 2: Sample the next node . . . V_2

Stream of edges

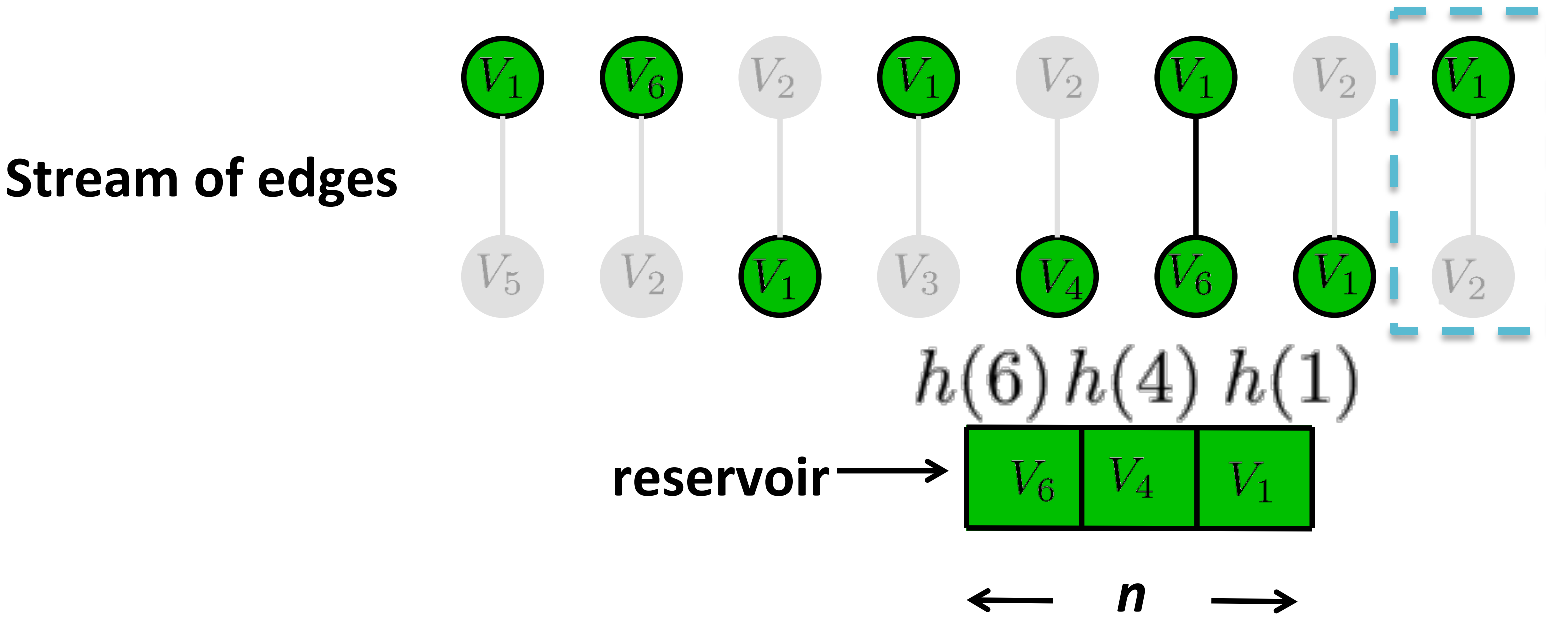


V_2 replaced V_5
$h(2) < h(5)$

$$h(6) < h(1) < h(2)$$

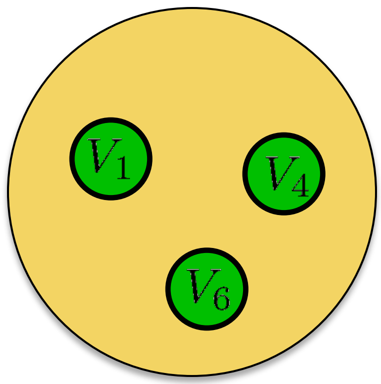
Streaming Uniform Node Sampling (RN) – Example

At the end of the sequential pass . . .

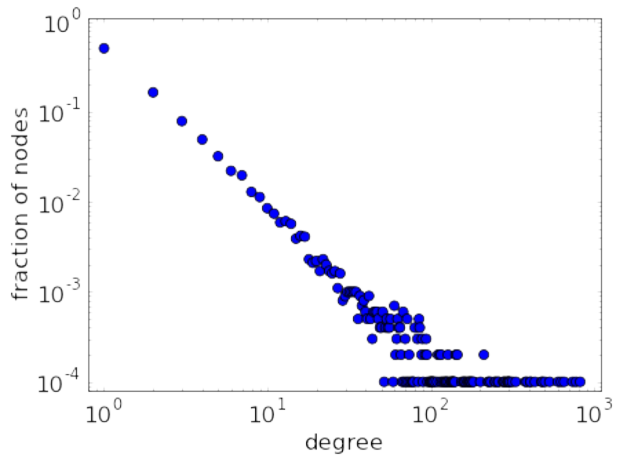


$$h(6) < h(4) < h(1)$$

- at the end of the sequential pass, the current set of *n nodes* is output as the final sample



Sampled Set of Nodes



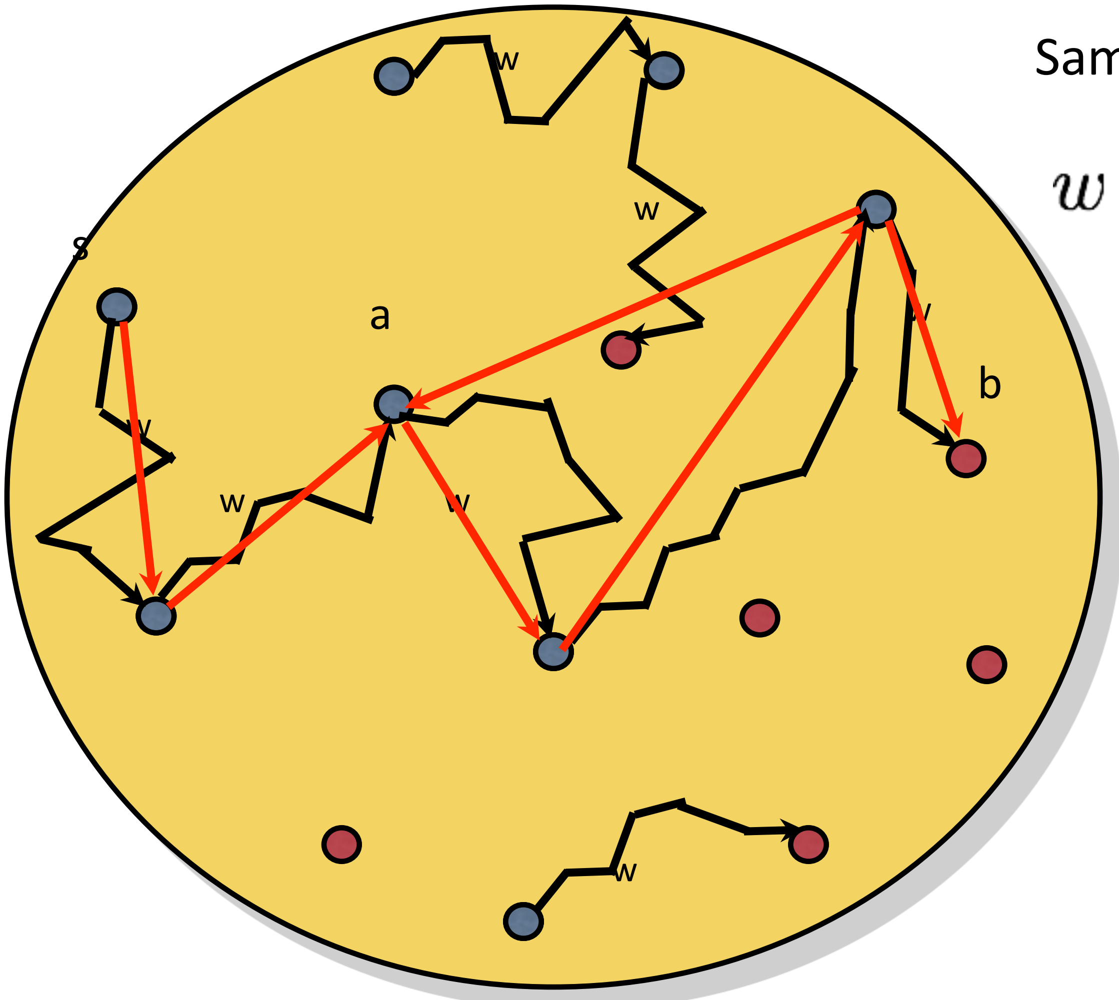
Sampling methods under data streaming access assumption

- Streaming Uniform Edge Sampling
  - Extends traditional random edge sampling (RE) to streaming access
- Streaming Uniform Node Sampling
  - Extends traditional random node sampling (RN) to streaming access
- Multiple Random Walk Sampling
  - Extends traditional random walk to streaming access

Multiple Random Walk Sampling

- Goal: Perform a random walk to estimate node pagerank – [Sarma'08]
  - Determine Ranking of nodes in a graph (run daily by commercial search engines)
- Sample a set of nodes in one pass with probability α
- Perform short walks from sampled centers
- Concatenate and merge walks

Short Walks with Sampling



Sample α fraction of nodes

w passes -w length walks

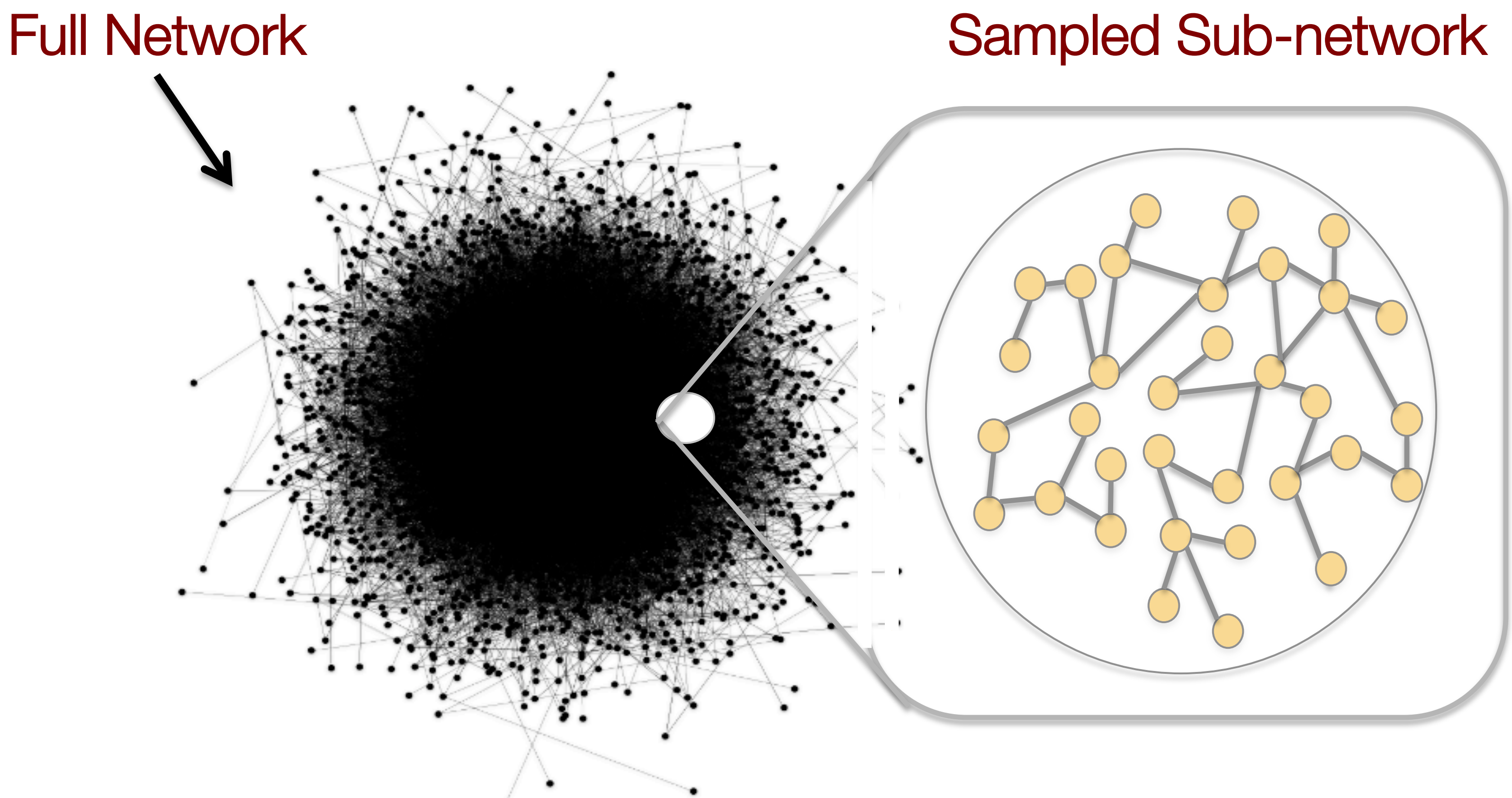
Merge and extend short walks!

Source: *Sarma et.al 2008*

TASK 2

Representative Sub-network Sampling

Representative Sub-network Sampling



- Select a representative sampled sub-network

- The sample is representative if its structural properties are similar to the full network

Estimate node/edge properties in original network

Sample representative subgraph/subnetwork

Estimate frequency of subgraph patterns

Data Access Assumption

	Task 1	Task 2	Task 3
Full Access	✓	✓	
Restricted Access	✓		
Data Stream Access	✓		

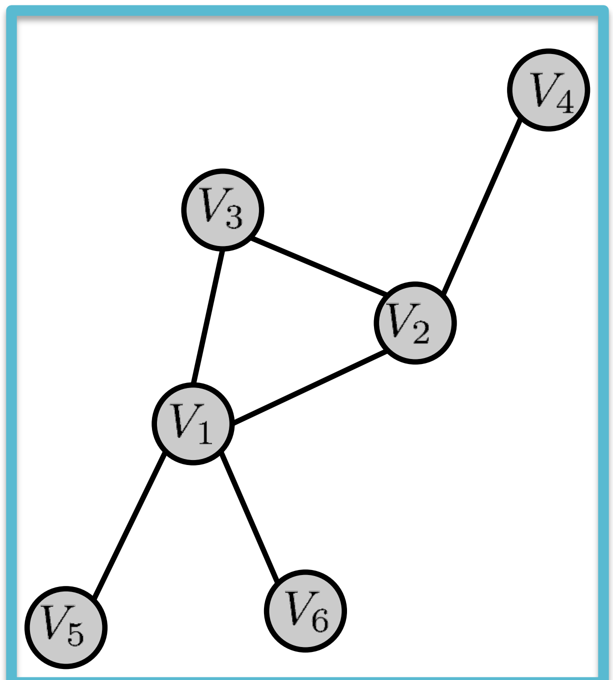
Sampling Objective

Sampling methodology

Sampling methods under full access assumptions

- Node sampling
  - Starts by sampling nodes
  - Add all edges between sampled nodes (Induced subgraph)
- Edge Sampling
  - Uniform edge sampling
  - Uniform Edge Sampling with graph induction
- Exploration Sampling
  - Graph traversal techniques
  - Random walk techniques
- Sampling the network community structure
  - Graph traversal to maximize the sample expansion
- Metropolis-Hastings sampling
  - Search the space for the best representative sub-network

- Assume we have the following network
- **Goal:** sample a representative sub-network of size = 4 nodes

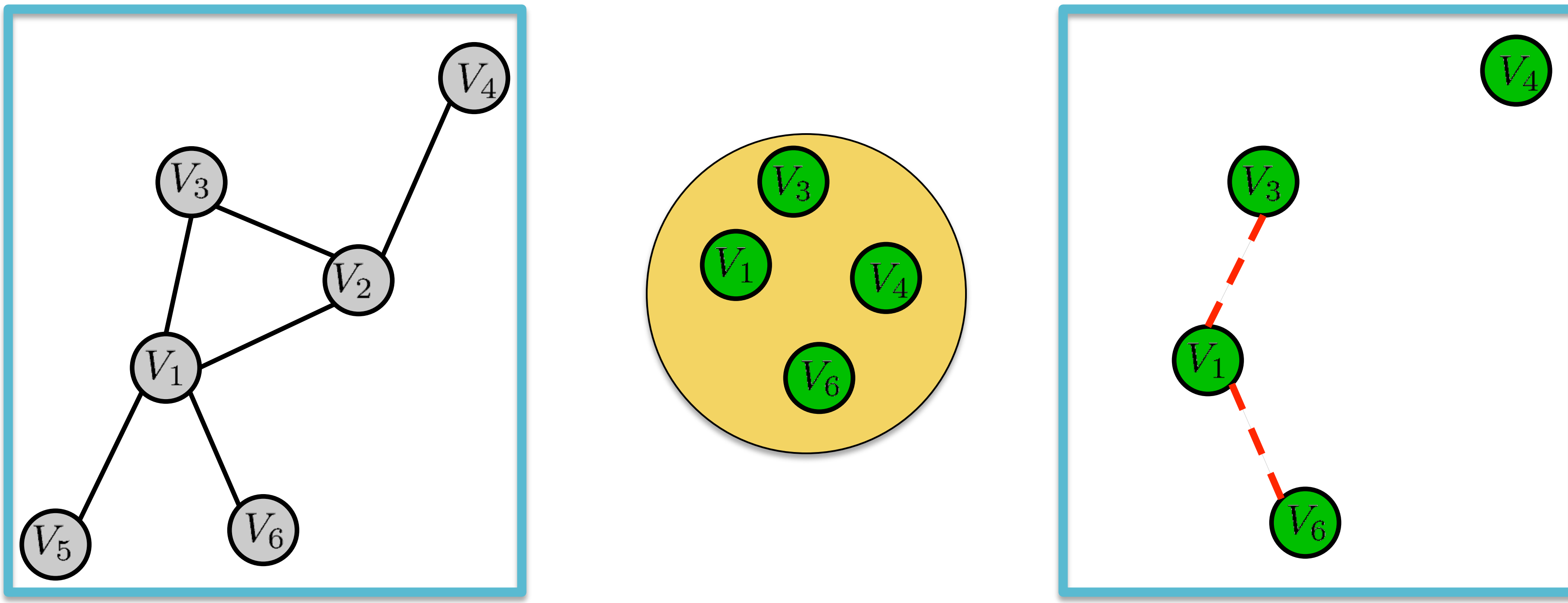


Original Network

Sampling methods under full access assumptions

- Node sampling
  - Starts by sampling nodes
  - Add all edges between sampled nodes (Induced subgraph)
- Edge Sampling
  - Uniform edge sampling
  - Uniform Edge Sampling with graph induction
- Exploration Sampling
  - Graph traversal techniques
  - Random walk techniques
- Sampling the network community structure
  - Graph traversal to maximize the sample expansion
- Metropolis-Hastings sampling
  - Search the space for the best representative sub-network

Node Sampling



Original Network | Sampled Nodes | Sampled Sub-network

- - - - *Edges added by graph induction*

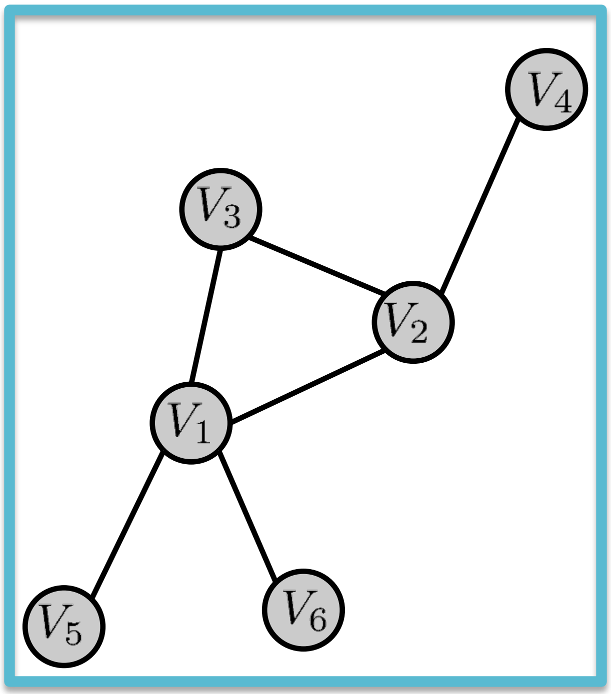
Node Sampling (NS)

- Node sampling samples nodes uniformly
- Generally biased to low degree nodes
- Sampled sub-network may include isolated nodes (zero degree)
- The sampled sub-network typically fails to preserve many properties of the original network
  - diameter, hop-plot, clustering co-efficient, and centrality values of vertices.

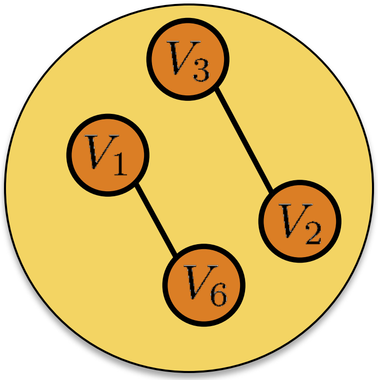
Sampling methods under full access assumptions

- Node sampling
  - Starts by sampling nodes
  - Add all edges between sampled nodes (Induced subgraph)
- Edge Sampling
  - Uniform edge sampling
  - Uniform Edge Sampling with graph induction
- Exploration Sampling
  - Graph traversal techniques
  - Random walk techniques
- Sampling the network community structure
  - Graph traversal to maximize the sample expansion
- Metropolis-Hastings sampling
  - Search the space for the best representative sub-network

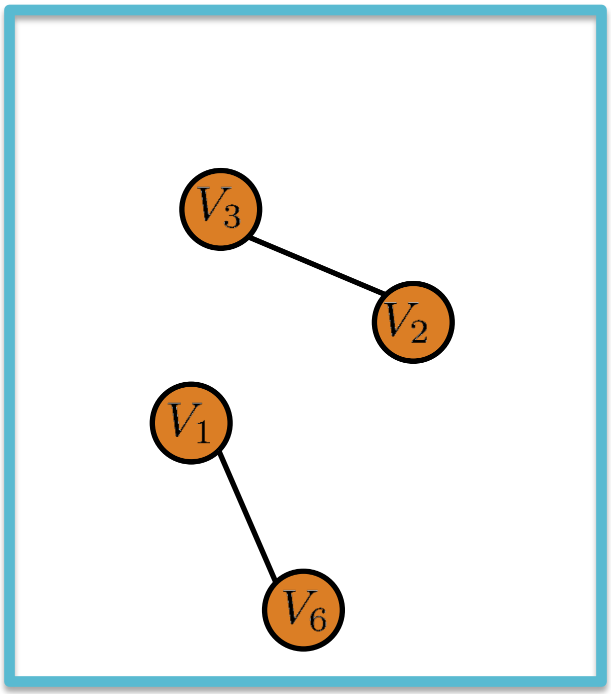
Uniform Edge Sampling (ES)



Original Network



Sampled Edges

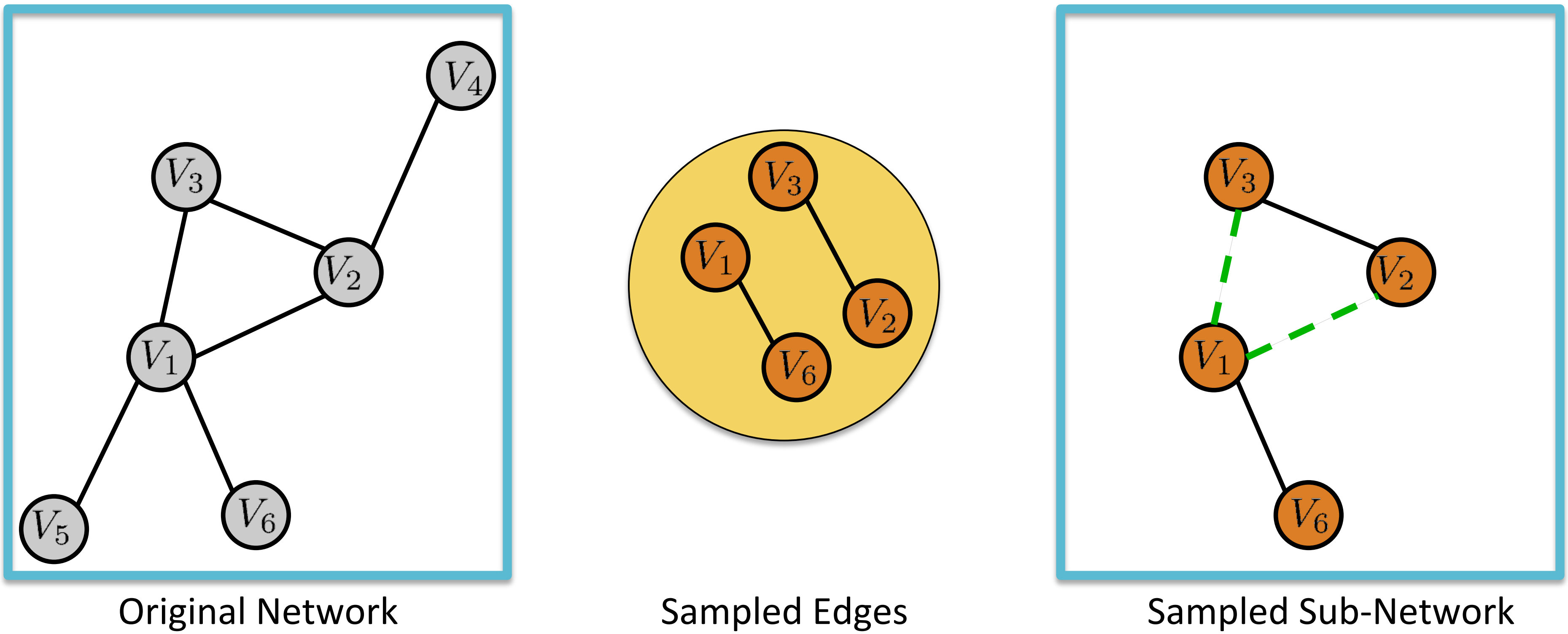


Sampled Sub-Network

Edge Sampling (ES)

- Edge sampling samples nodes proportional to their degree
- Generally biased to high degree nodes (hub nodes)
- The sampled sub-network typically <u>fails</u> to preserve many properties of the original network
    - diameter, hop-plot, clustering co-efficient, and centrality values of vertices.

Uniform Edge Sampling with graph induction (ES-i) [Ahmed '13]



Edges added by graph induction

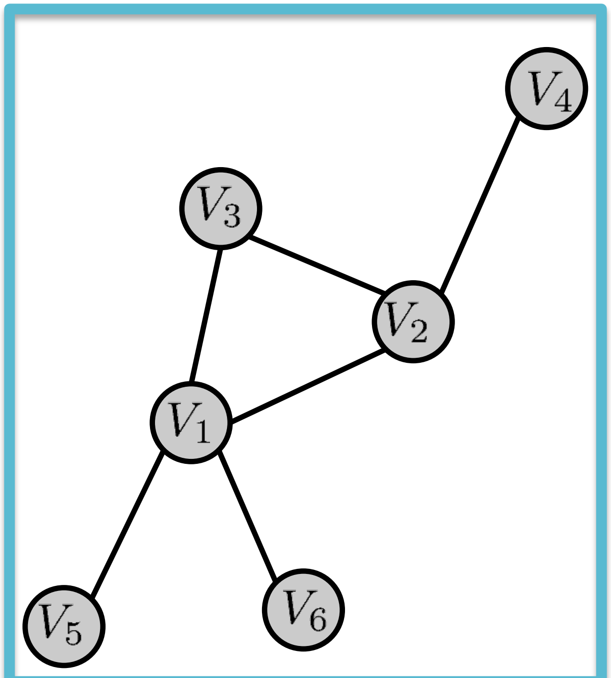
Edge Sampling with graph induction (ES-i)

- Similar to the edge sampling (ES)
  - ES-i samples nodes proportional to their degree
  - Generally biased to high degree nodes (hub nodes)
- Due to the additional graph induction step
  - The sampled sub-network preserves many properties of the original network
    - degree, diameter, hop-plot, clustering co-efficient, and centrality values of vertices.

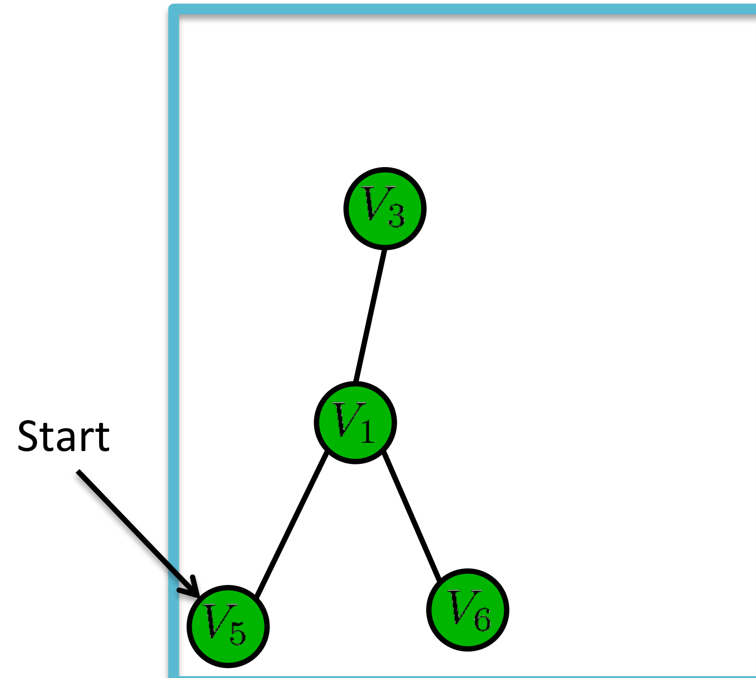
Sampling methods under full access assumptions

- Node sampling
  - Starts by sampling nodes
  - Add all edges between sampled nodes (Induced subgraph)
- Edge Sampling
  - Uniform edge sampling
  - Uniform Edge Sampling with graph induction
- Exploration Sampling
  - Graph traversal techniques
  - Random walk techniques
- Sampling the network community structure
  - Graph traversal to maximize the sample expansion
- Metropolis-Hastings sampling
  - Search the space for the best representative sub-network

Exploration Sampling – Breadth First



Original Network



Sampled Sub-Network

Sampled sub-network consists of all nodes/edges visited

Exploration Sampling

- Generally biased to high degree nodes (hub nodes)
- The sampled sub-network can preserve the diameter of the network if enough nodes are visited
- The sampled sub-network usually fails to preserve clustering co-efficient
- One solution: induce the sampled sub-network

Sampling methods under full access assumptions

- Node sampling
  - Starts by sampling nodes
  - Add all edges between sampled nodes (Induced subgraph)
- Edge Sampling
  - Uniform edge sampling
  - Uniform Edge Sampling with graph induction
- Exploration Sampling
  - Graph traversal techniques
  - Random walk techniques
- Sampling the network community structure
  - Graph traversal to maximize the sample expansion
- Metropolis-Hastings sampling
  - Search the space for the best representative sub-network

Sampling Community Structure [Maiya'10]

- Sampling a sub-network representative of the original network community structure
  - Expansion Sampling (XS)

- Expansion Sampling Algorithm:
  - <u>Step1:</u> Starts with a random vertex *u*, add *u* to the sample set *S*

    S = S U {u}

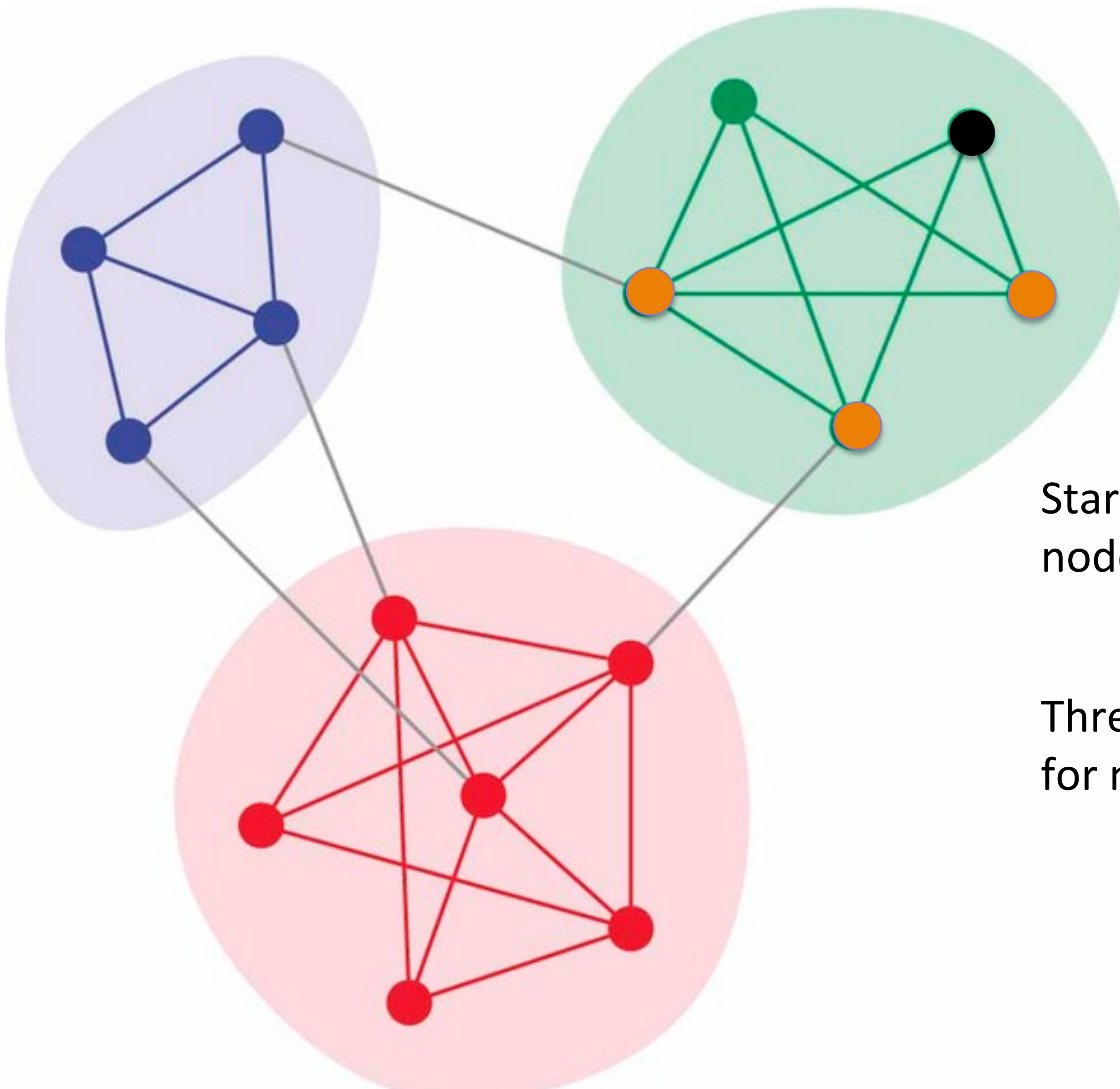
  - <u>Step2:</u> Choose *v* from *S's* neighborhood, s.t. *v* maximizes

    |Neigh(v) – {Neigh(S) U S}|

  - <u>Step3:</u> Add *v* to *S*

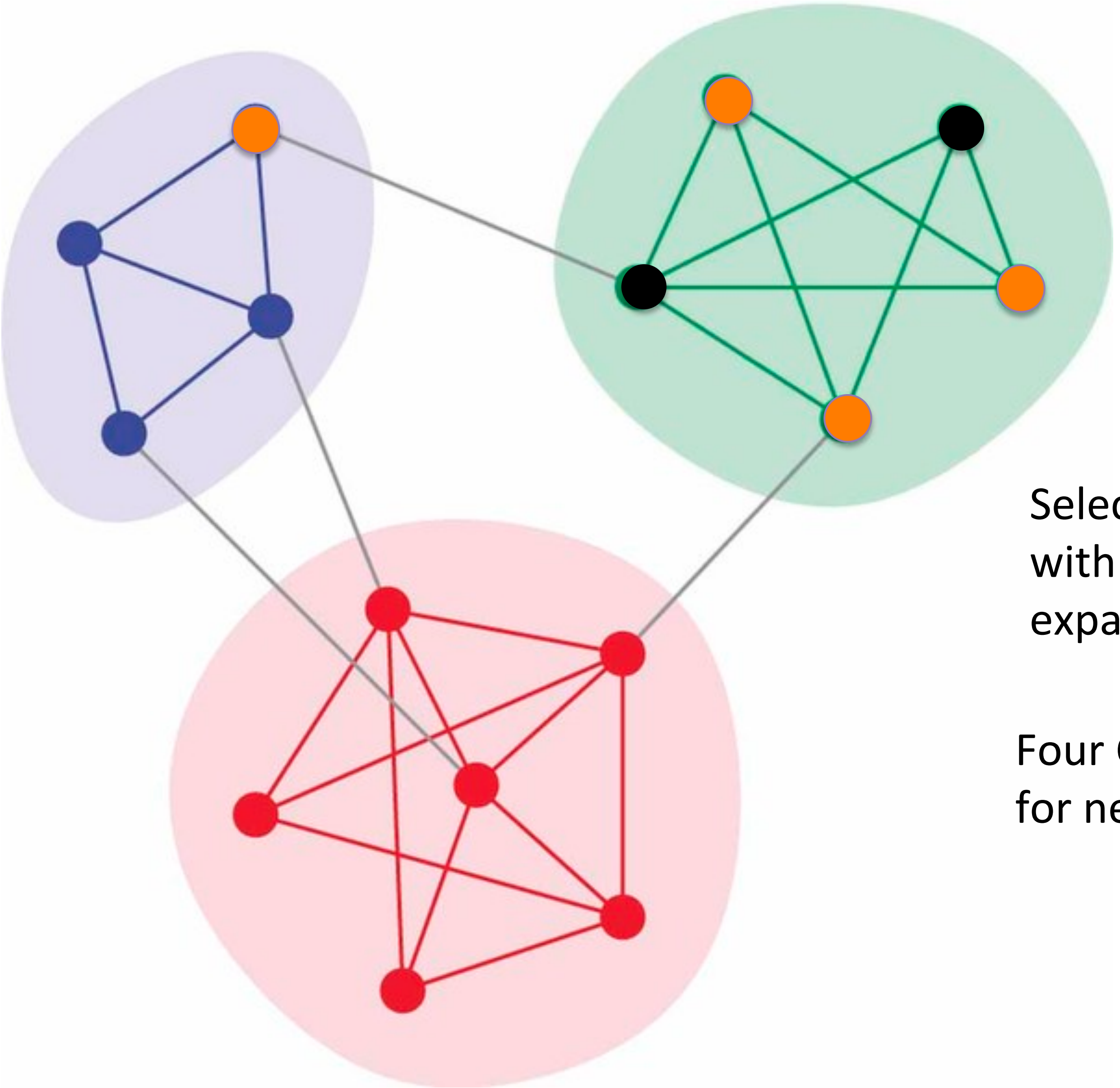
    S = S U {v}

  - Repeat Step 2 and 3 until **|S| = k**



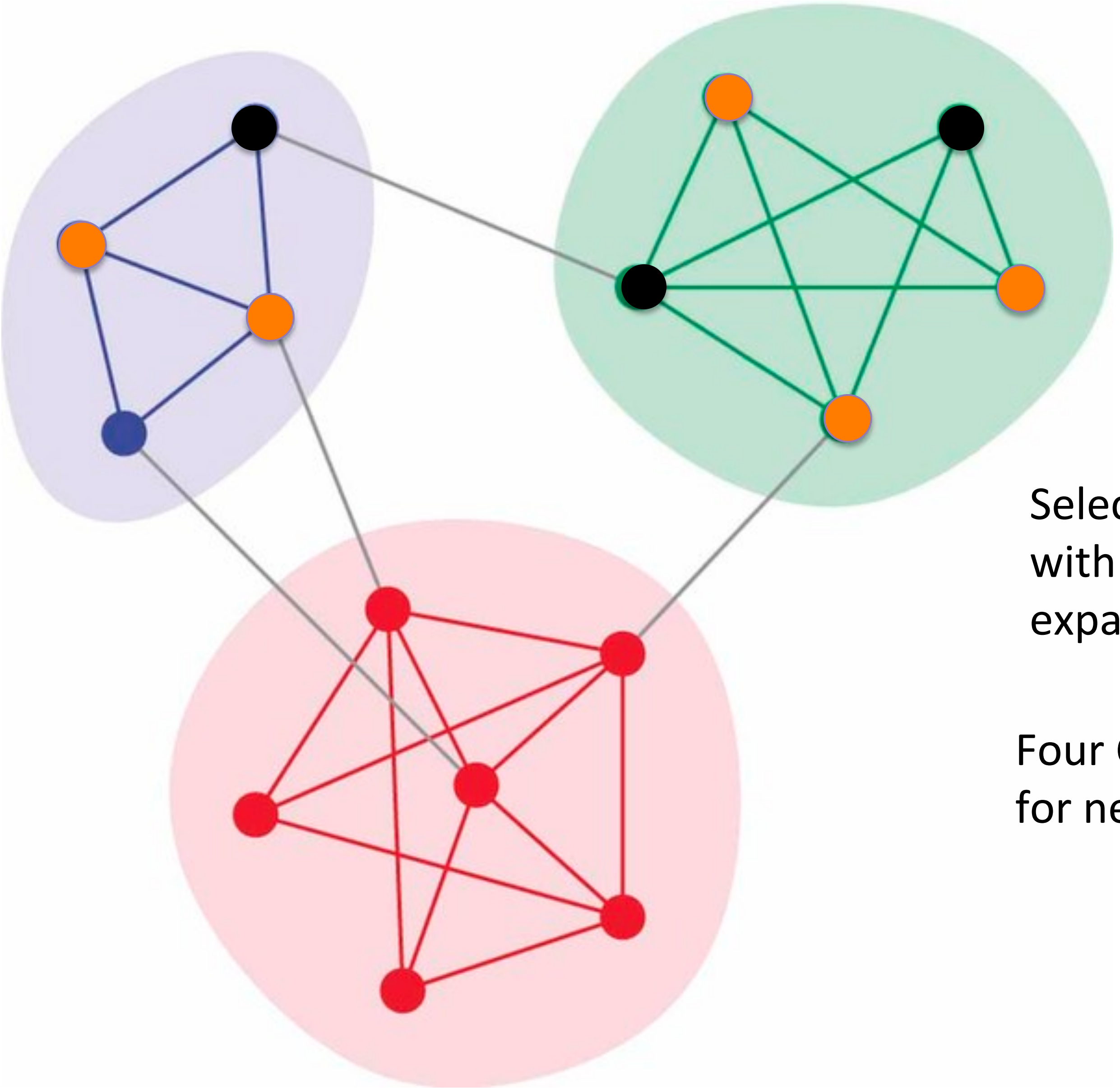
Start with random node

Three Candidates for next step



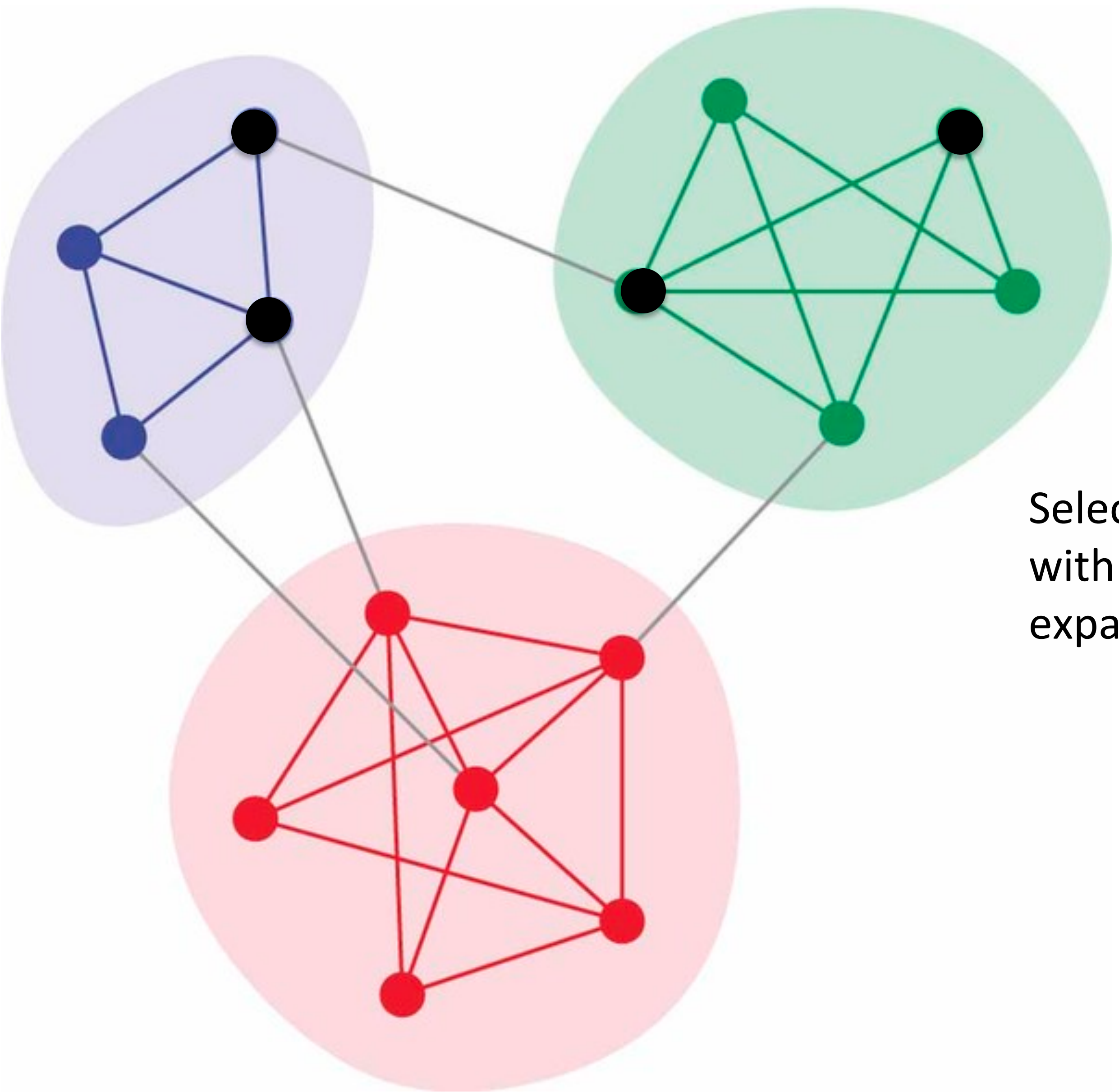
Select the one with maximum expansion

Four Candidates for next step



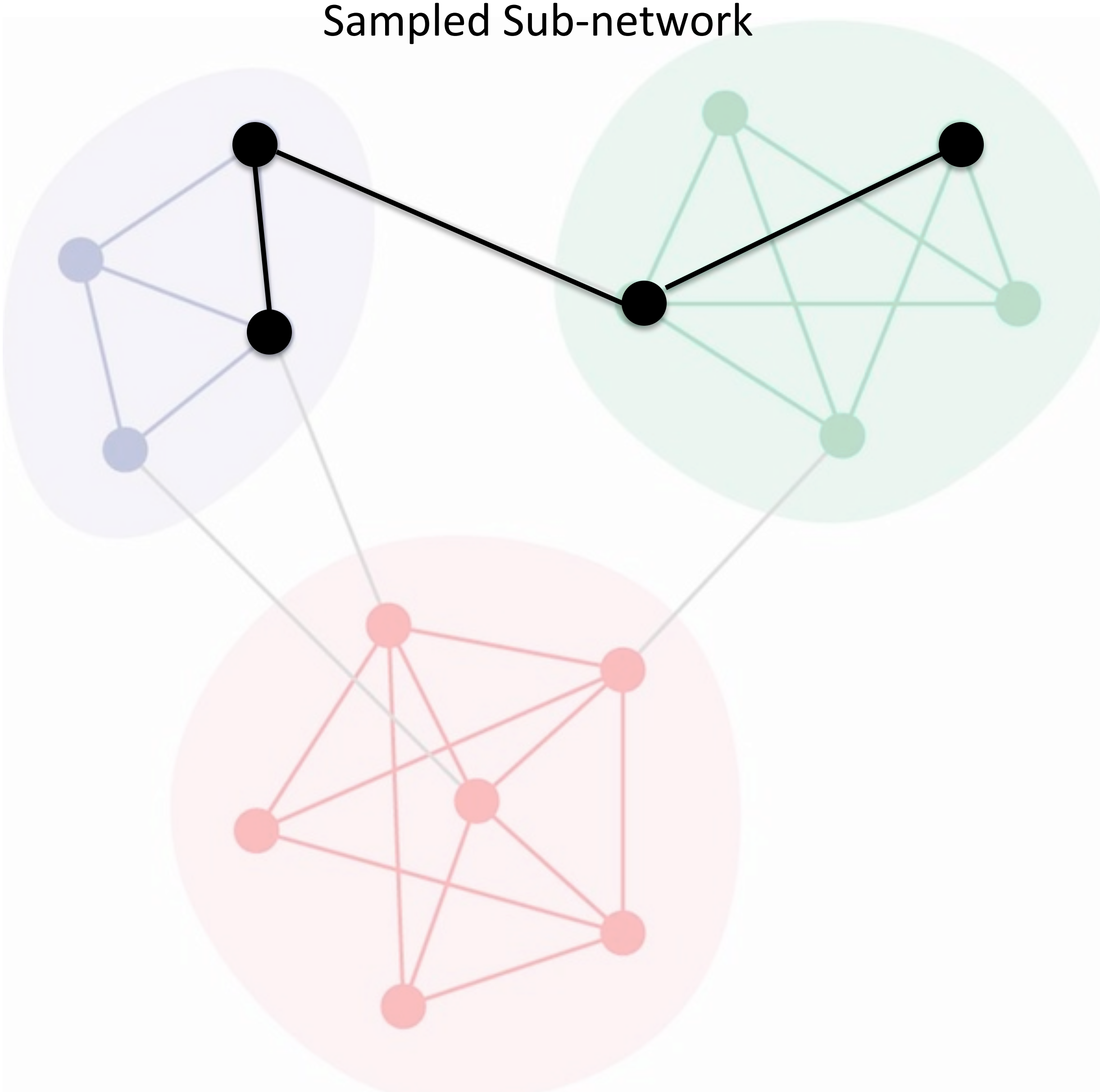
Select the one with maximum expansion

Four Candidates for next step



Select the one with maximum expansion

Sampled Sub-network



Sampling methods under full access assumptions

- Node sampling
  - Starts by sampling nodes
  - Add all edges between sampled nodes (Induced subgraph)
- Edge Sampling
  - Uniform edge sampling
  - Uniform Edge Sampling with graph induction
- Exploration Sampling
  - Graph traversal techniques
  - Random walk techniques
- Sampling the network community structure
  - Graph traversal to maximize the sample expansion
- Metropolis-Hastings sampling
  - Search the space for the best representative sub-network (Hubler et al.)

Estimate node/edge properties in original network

Sample representative subgraph/subnetwork

Estimate frequency of subgraph patterns

Data Access Assumption

	Task 1	Task 2	Task 3
Full Access	✓	✓	
Restricted Access	✓	✓	
Data Stream Access	✓		

Sampling Objective

Sampling methodology

Sampling methods under restricted access assumptions

- Exploration Sampling
  - Graph traversal techniques
  - Random walk techniques

- Sampling nodes or edges is not feasible under restricted access assumption

Estimate node/edge properties in original network

Sample representative subgraph/subnetwork

Estimate frequency of subgraph patterns

	Task 1	Task 2	Task 3
Full Access	✓	✓	
Restricted Access	✓	✓	
Data Stream Access	✓	✓	

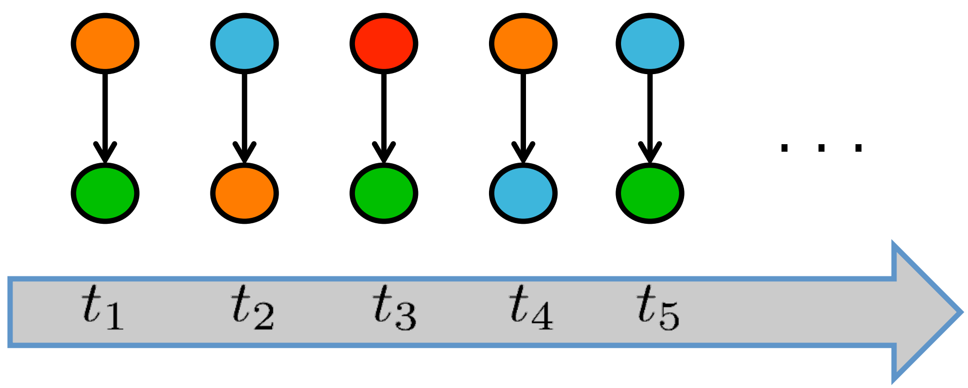
Data Access Assumption

Sampling Objective

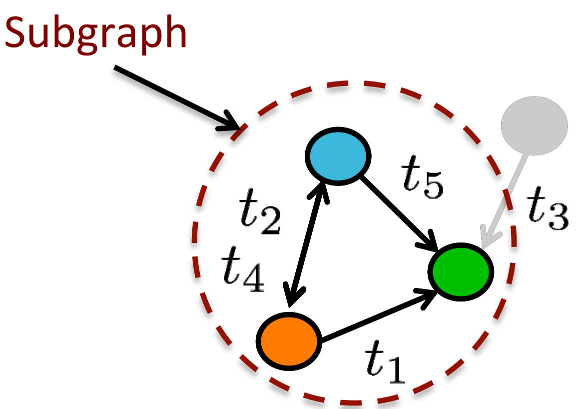
Sampling methodology

Sampling under data streaming access assumption

- Sampling a subgraph (sub-network) while the graph is streaming as a sequence of edges of any arbitrary order



Stream of edges over time



Graph with timestamps

Sampling methods under data streaming access assumption

- Streaming Uniform Node Sampling
- Streaming Uniform Edge Sampling
- Partially Induced Edge sampling (PIES)
- Exploration Sampling
  - Streaming Breadth First Search

Sampling methods under data streaming access assumption

- Streaming Uniform Node Sampling
  - Similar to **Task 1** but adding the edges from the graph induction

- Streaming Uniform Edge Sampling

- Partially Induced Edge sampling (PIES)

- Exploration Sampling
  - Streaming Breadth First Search

Sampling methods under data streaming access assumption

- Streaming Uniform Node Sampling
  - Similar to **Task 1** but adding the induced edges
- Streaming Uniform Edge Sampling
  - Similar to **Task 1**
- Partially Induced Edge sampling (PIES)
- Exploration Sampling
  - Streaming Breadth First Search

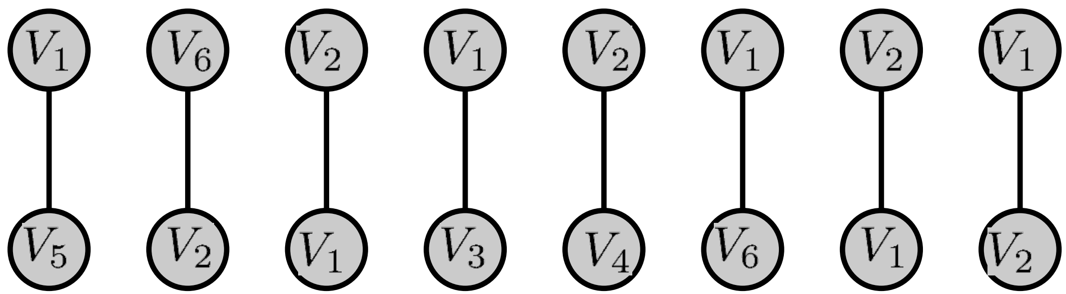
Sampling methods under data streaming access assumption

- Streaming Uniform Node Sampling
  - Similar to **Task 1** but adding the induced edges
- Streaming Uniform Edge Sampling
  - Similar to **Task 1**
- Partially Induced Edge sampling (PIES)
- Exploration Sampling
  - Streaming Breadth First Search

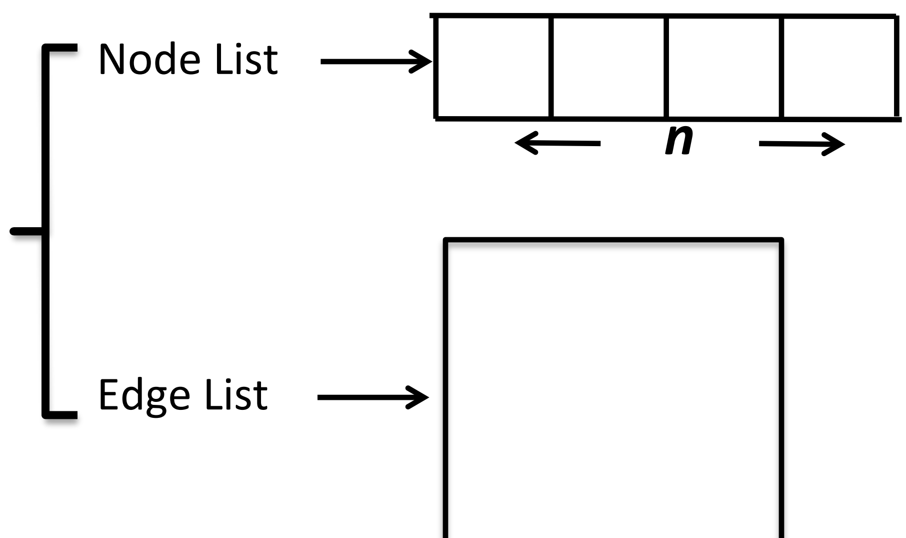
Example Partially Induced Edge Sampling (PIES) [Ahmed'13]

Step 0: Start with an empty reservoir

Stream of edges

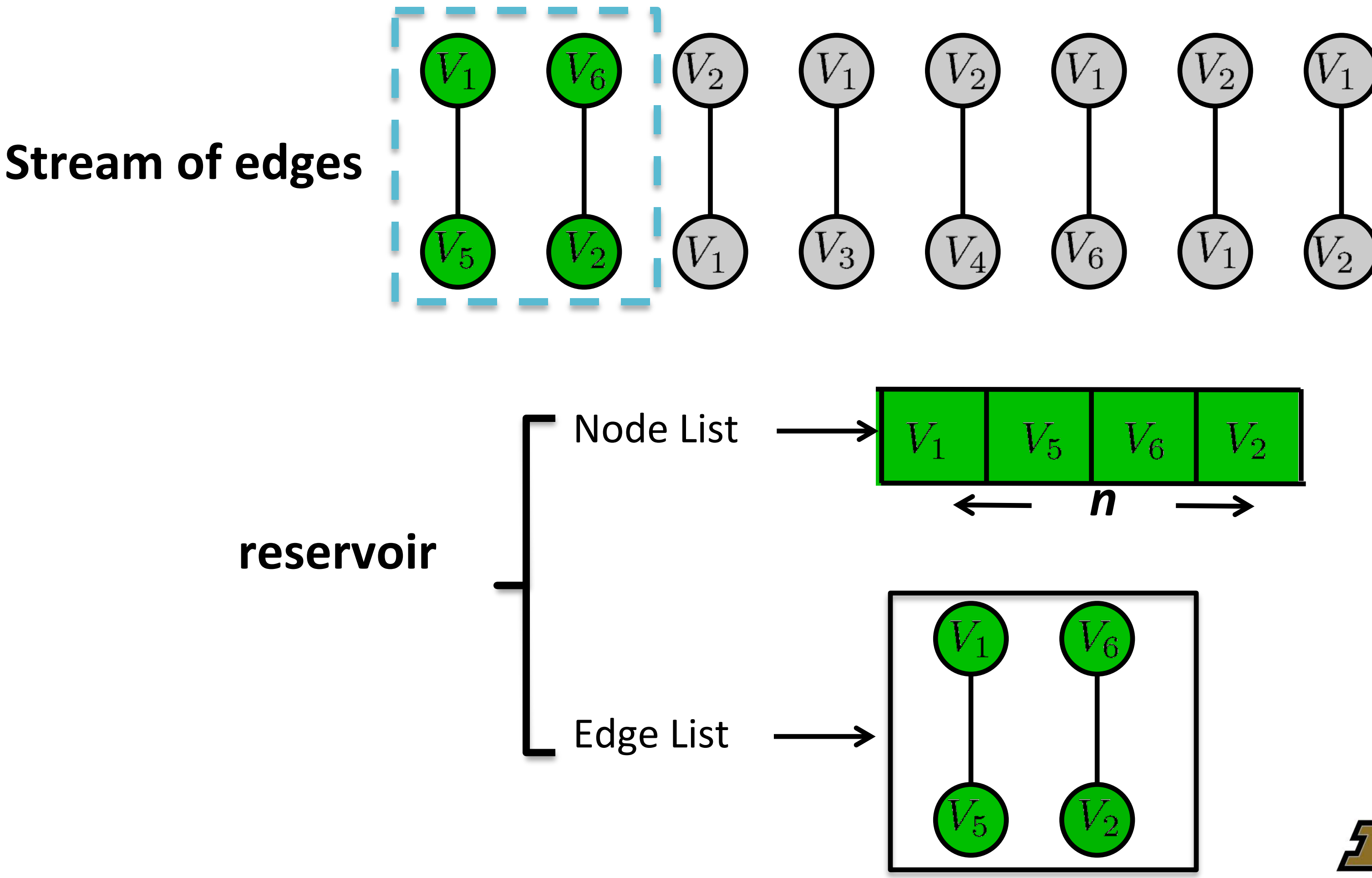


reservoir



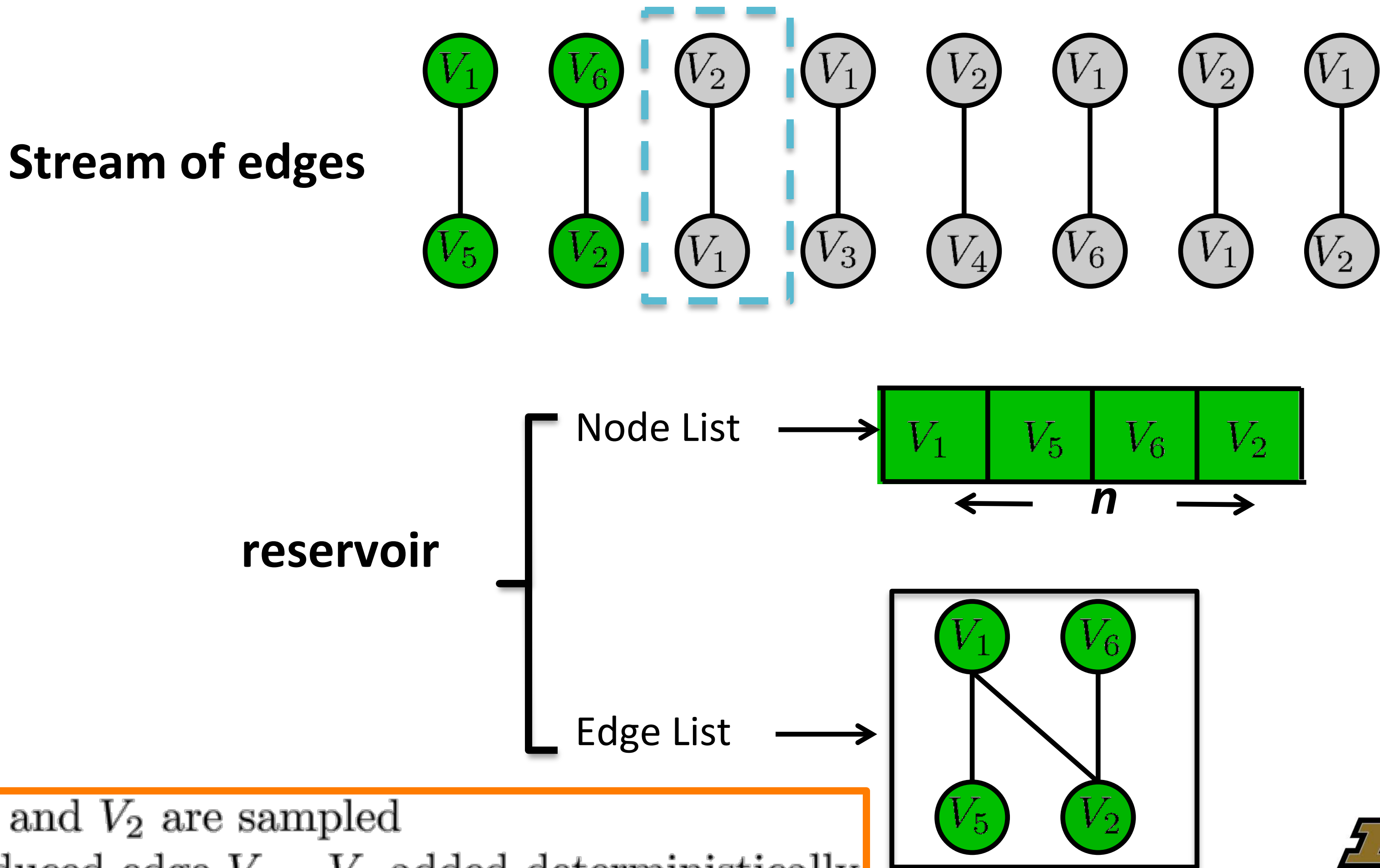
Example Partially Induced Edge Sampling (PIES) [Ahmed'13]

Step 1: Add the subgraph with first n nodes to reservoir



Example Partially Induced Edge Sampling (PIES) [Ahmed'13]

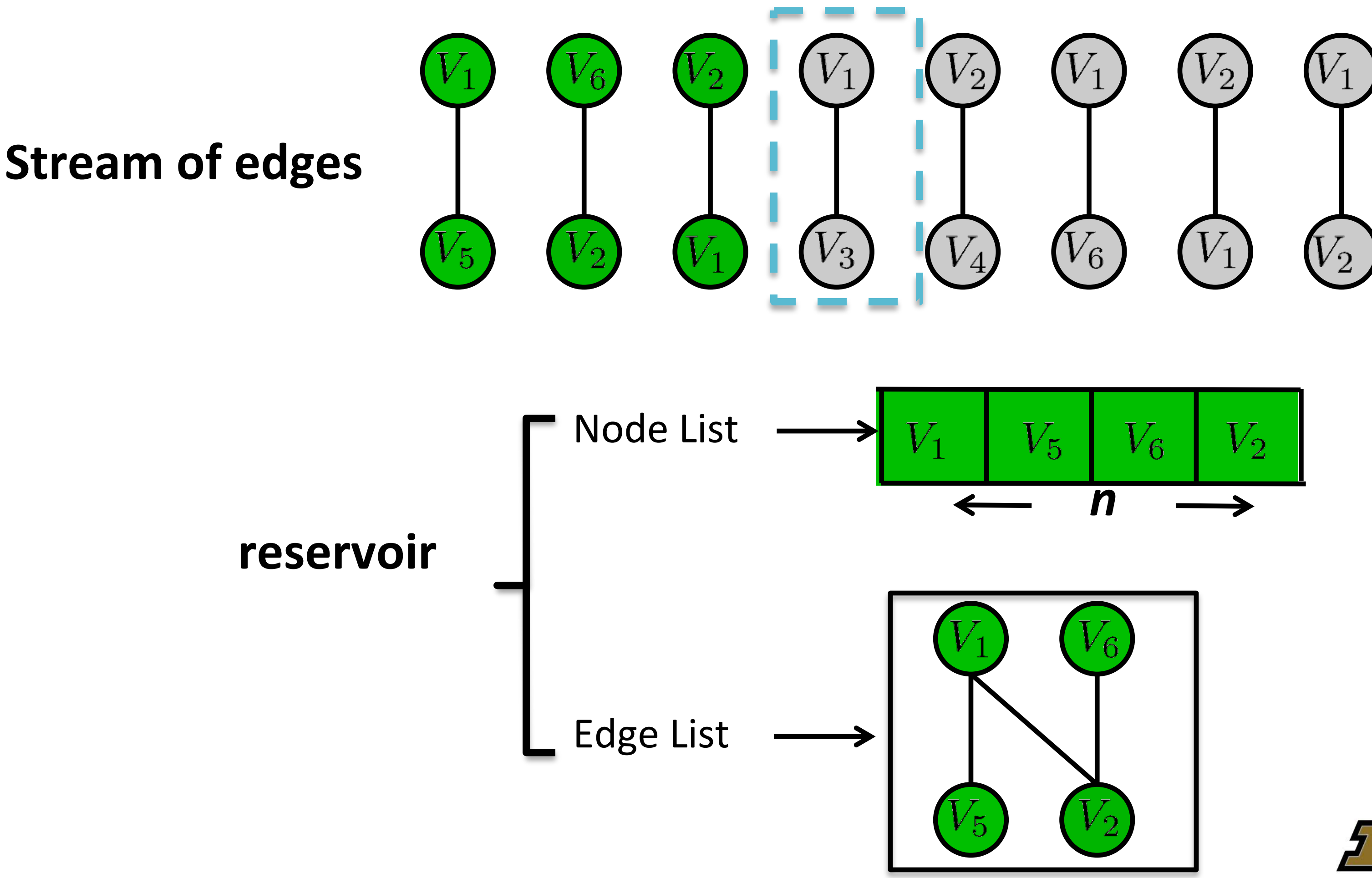
Step 3: Add the induced edge . . . $V_2 – V_1$



V_1 and V_2 are sampled
Induced edge $V_2 - V_1$ added deterministically

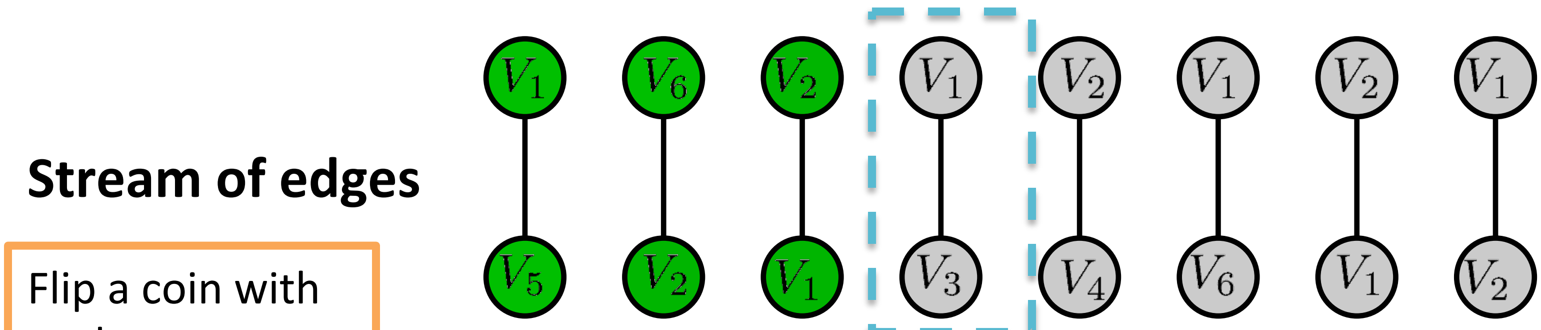
Example Partially Induced Edge Sampling (PIES) [Ahmed'13]

Step 3: Sample the next edge . . . $V_1 - V_3$ **With prob.** $P = n/k$



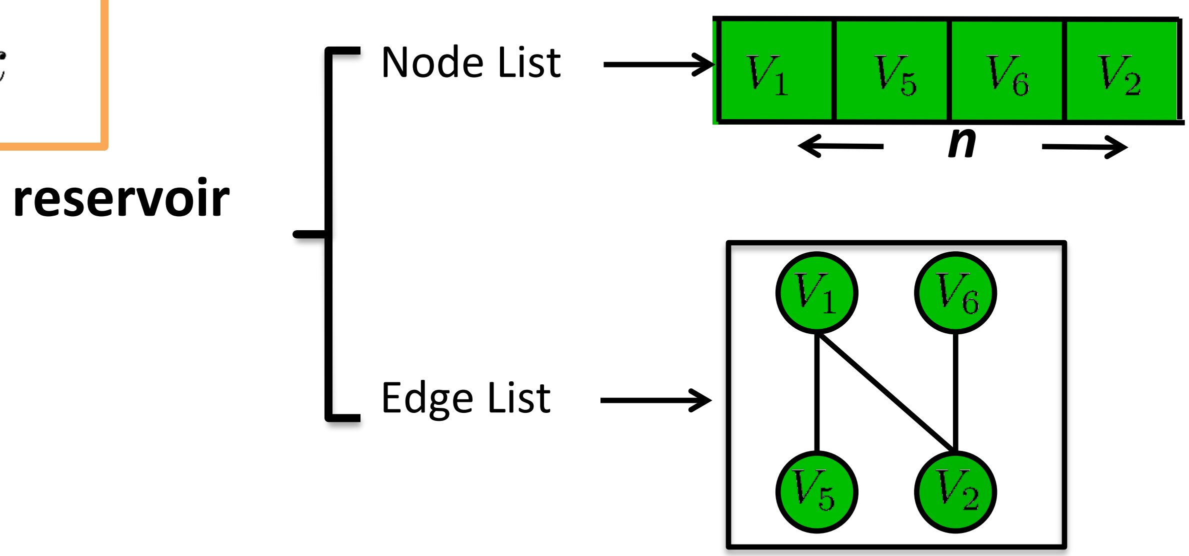
Example Partially Induced Edge Sampling (PIES) [Ahmed'13]

Step 3: Sample the next edge . . . $V_1 - V_3$ **With prob.** $P = n/k$



Flip a coin with prob.

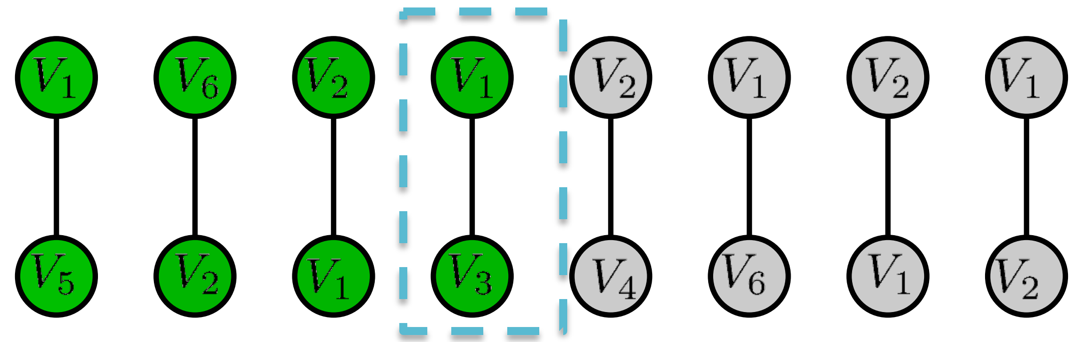
$$P = n/k$$



Example Partially Induced Edge Sampling (PIES) [Ahmed'13]

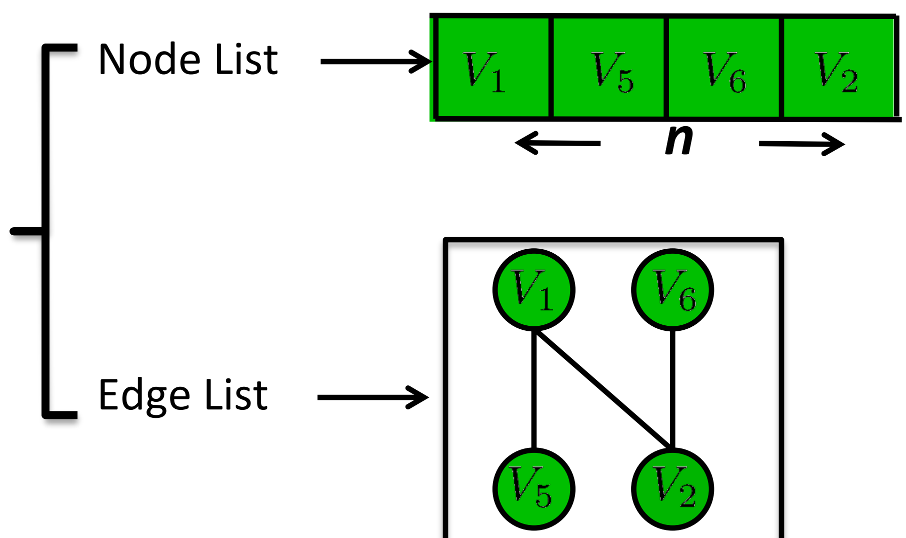
Step 3: Sample the next edge . . . $V_1 - V_3$ **With prob.** $P = n/k$

Stream of edges



Edge is selected

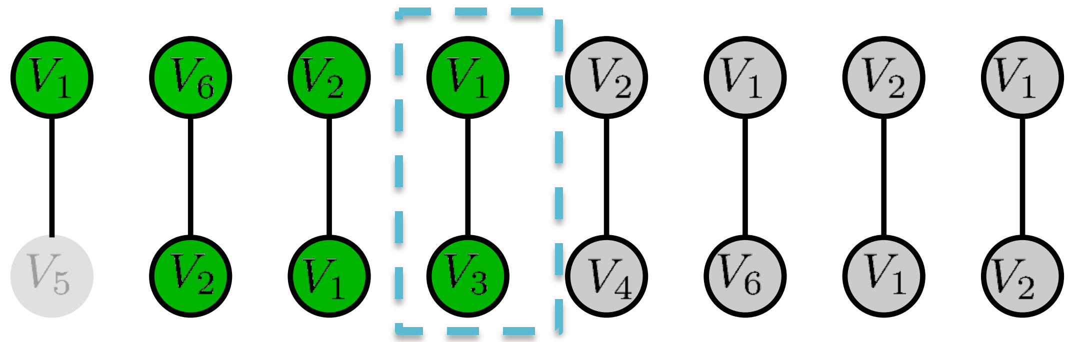
reservoir



Example Partially Induced Edge Sampling (PIES) [Ahmed'13]

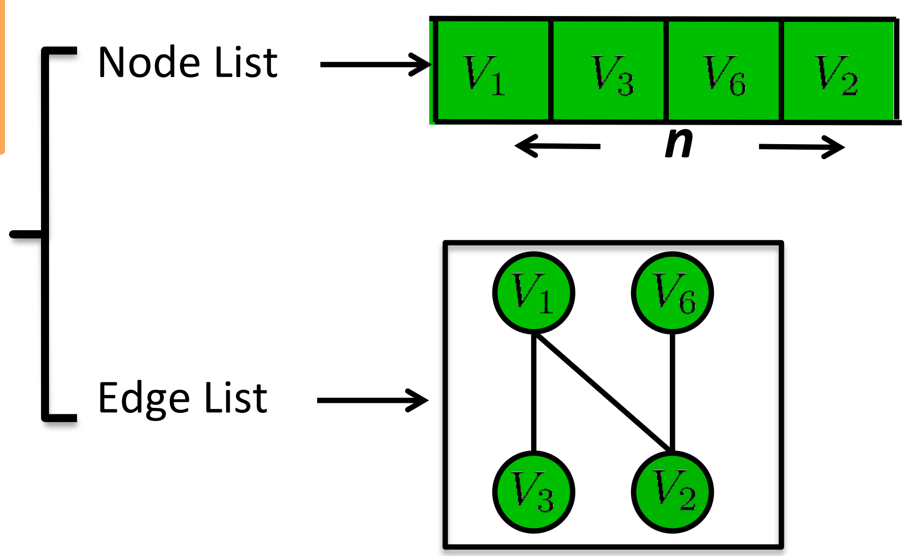
Step 3: Sample the next edge . . . $V_1 - V_3$ **With prob.** $P = n/k$

Stream of edges



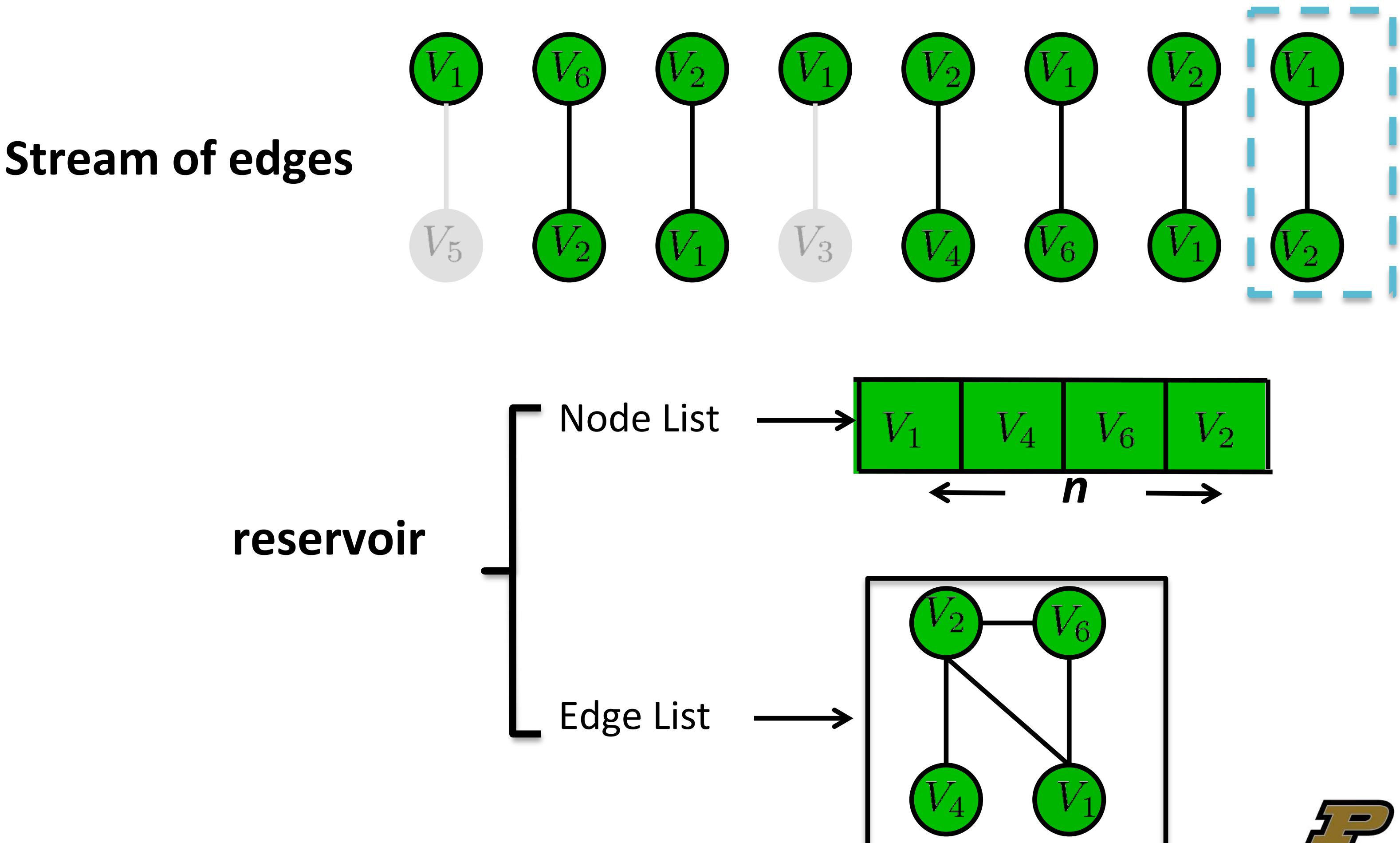
V_1 is already sampled
We need to insert V_3
V_3 replaces V_5 randmly

reservoir



Example Partially Induced Edge Sampling (PIES) [Ahmed'13]

At the end of the sequential pass . . .



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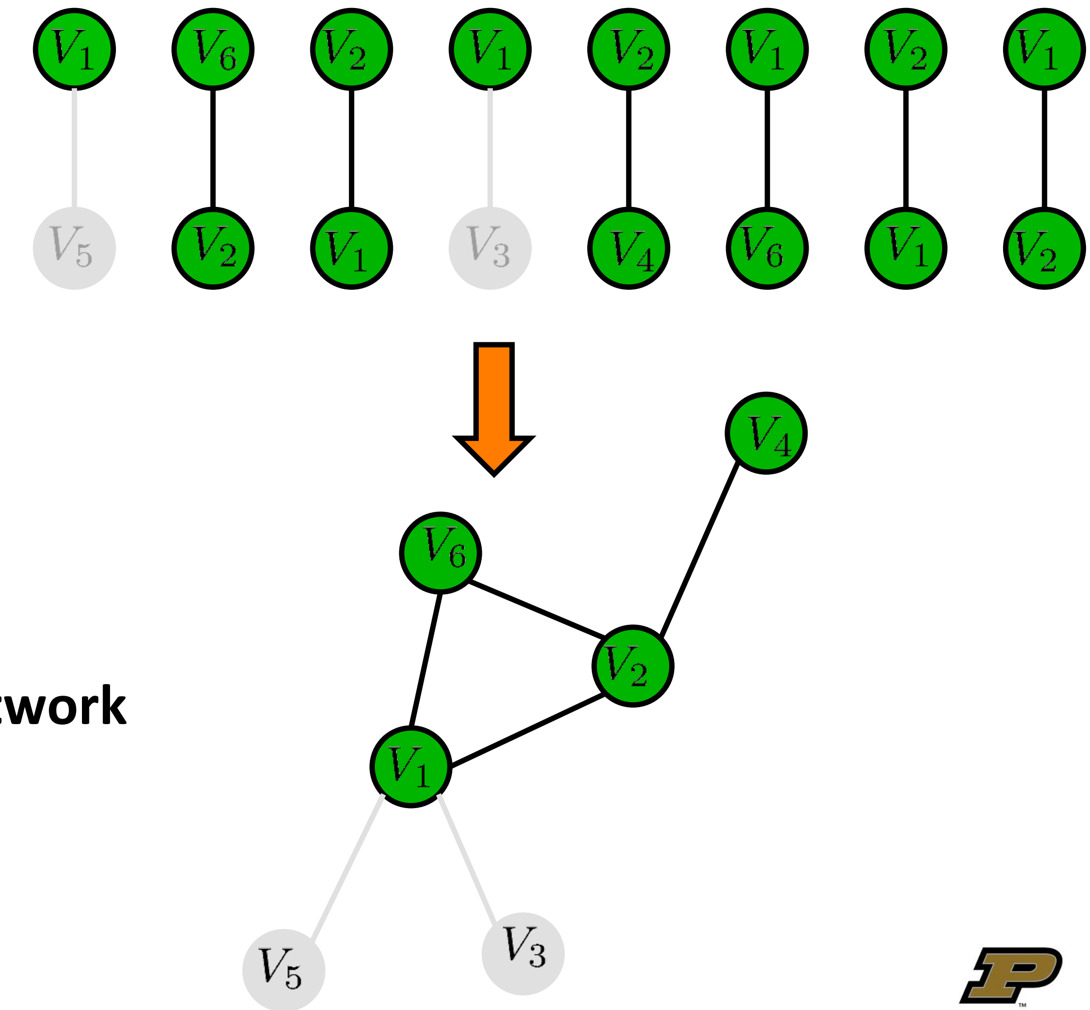
Example Partially Induced Edge Sampling (PIES) [Ahmed'13]

Stream of edges

Sampled Sub-network



Sampling methods under data streaming access assumption

- Streaming Uniform Node Sampling
  - Similar to **Task 1** but adding the induced edges
- Streaming Uniform Edge Sampling
  - Similar to **Task 1**
- Partially Induced Edge sampling (PIES)
- Exploration Sampling
  - Streaming Breadth First Search

Streaming Breadth First Search

- Streaming Breadth First Search in one pass
- Implements breadth first search in a window of consecutive edges
- Slide the window each time an edge is streaming in

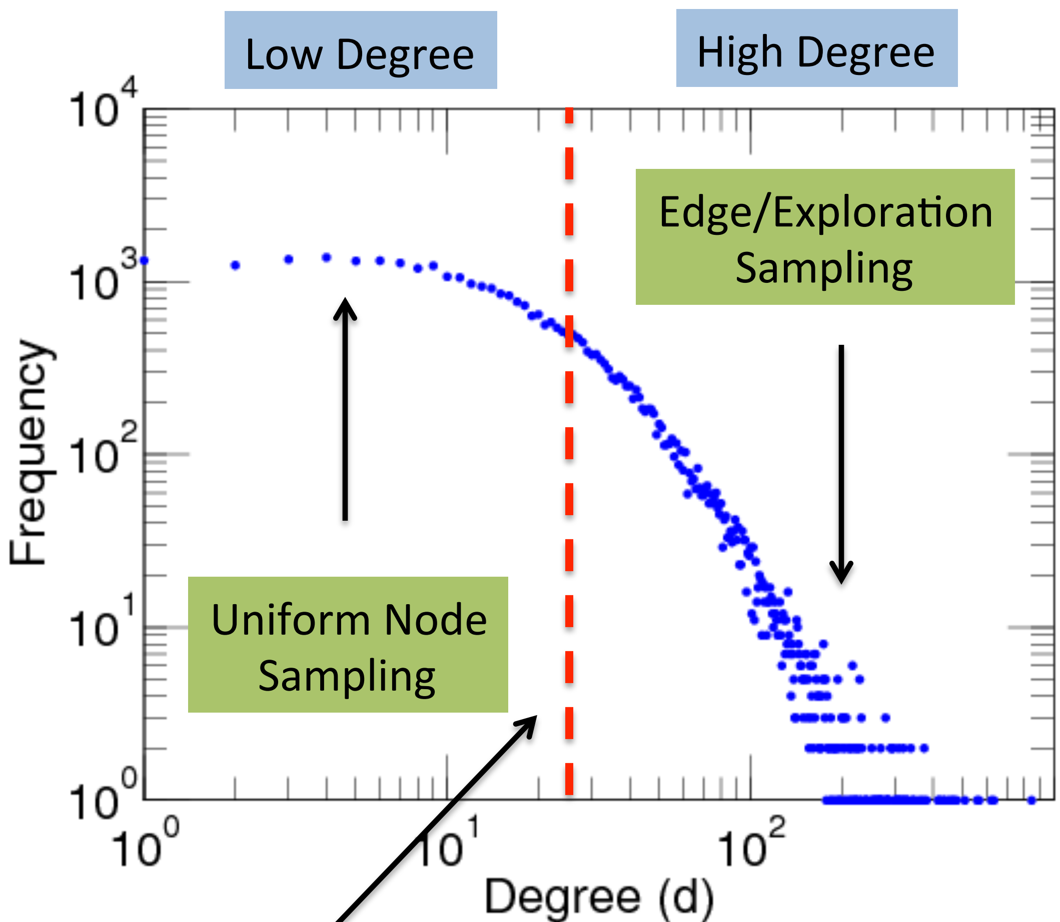
ANALYSIS & RESULTS

How different sampling methods sample from the degree distribution?

ArXiv Hep-PH

34K nodes

421K Edges



Avg. Degree = 24.4

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More Analysis

- Expected value of degree k in a sampled sub-network using uniform node sampling

$$E[f_D(k)] = f_D(k) \cdot n \cdot p$$
$$= f_D(k) \cdot \frac{n}{N}$$

- Expected value of degree k in a sampled sub-network using edge sampling with graph induction

$$E'[f_D(k)] = f_D(k) \cdot n \cdot p'$$
$$= f_D(k) \cdot n \cdot \frac{k}{2 \cdot |E|}$$

$$f_D(k) \cdot n \cdot \frac{k}{2 \cdot |E|} - f_D(k) \cdot \frac{n}{N} \geq 0$$

$$f_D(k) \cdot \frac{n}{N} \cdot \frac{k}{k_{avg}} - f_D(k) \cdot \frac{n}{N} \geq 0$$

$$k \geq k_{avg}$$

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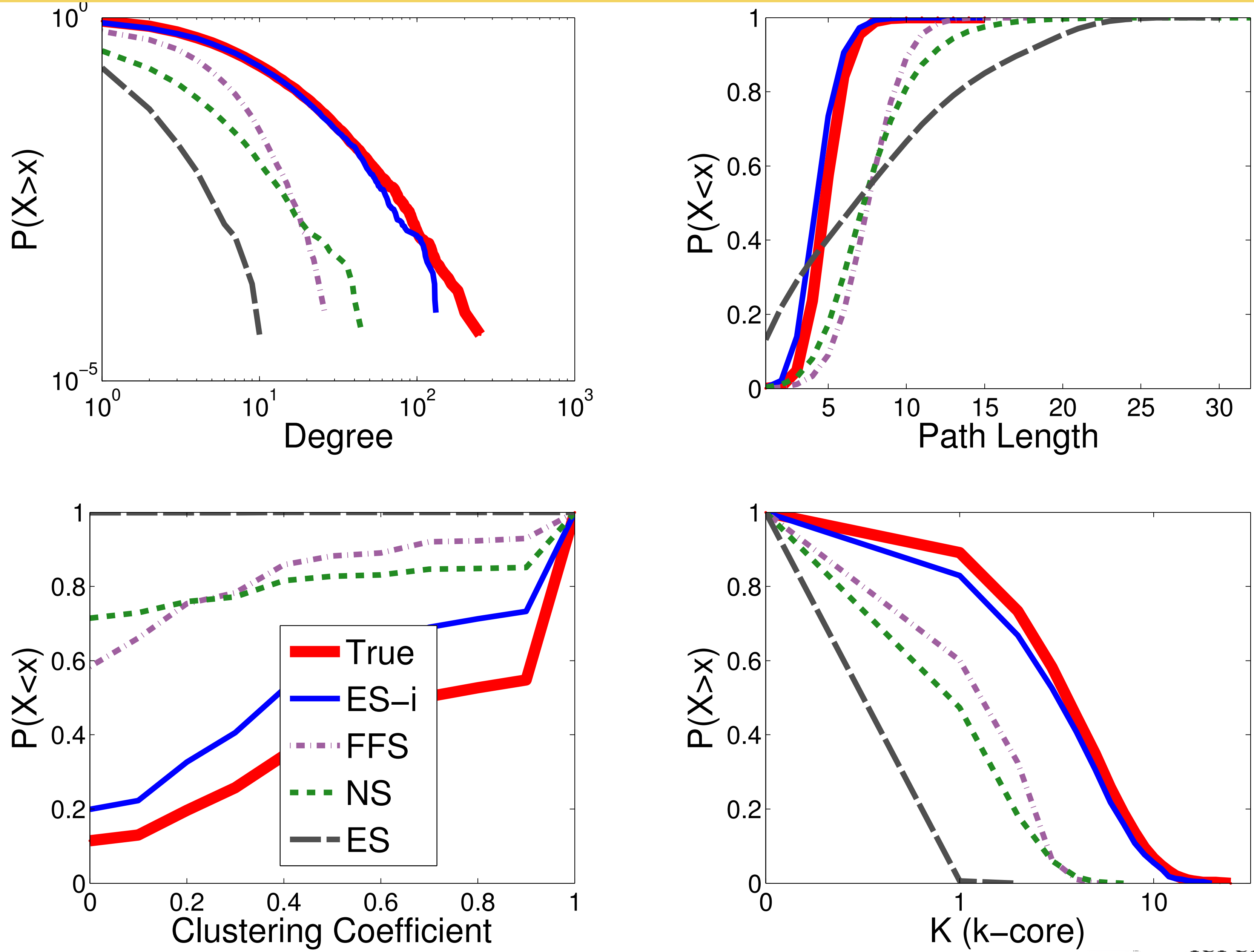
Edge sampling with graph induction (Es-i) performs better than other methods



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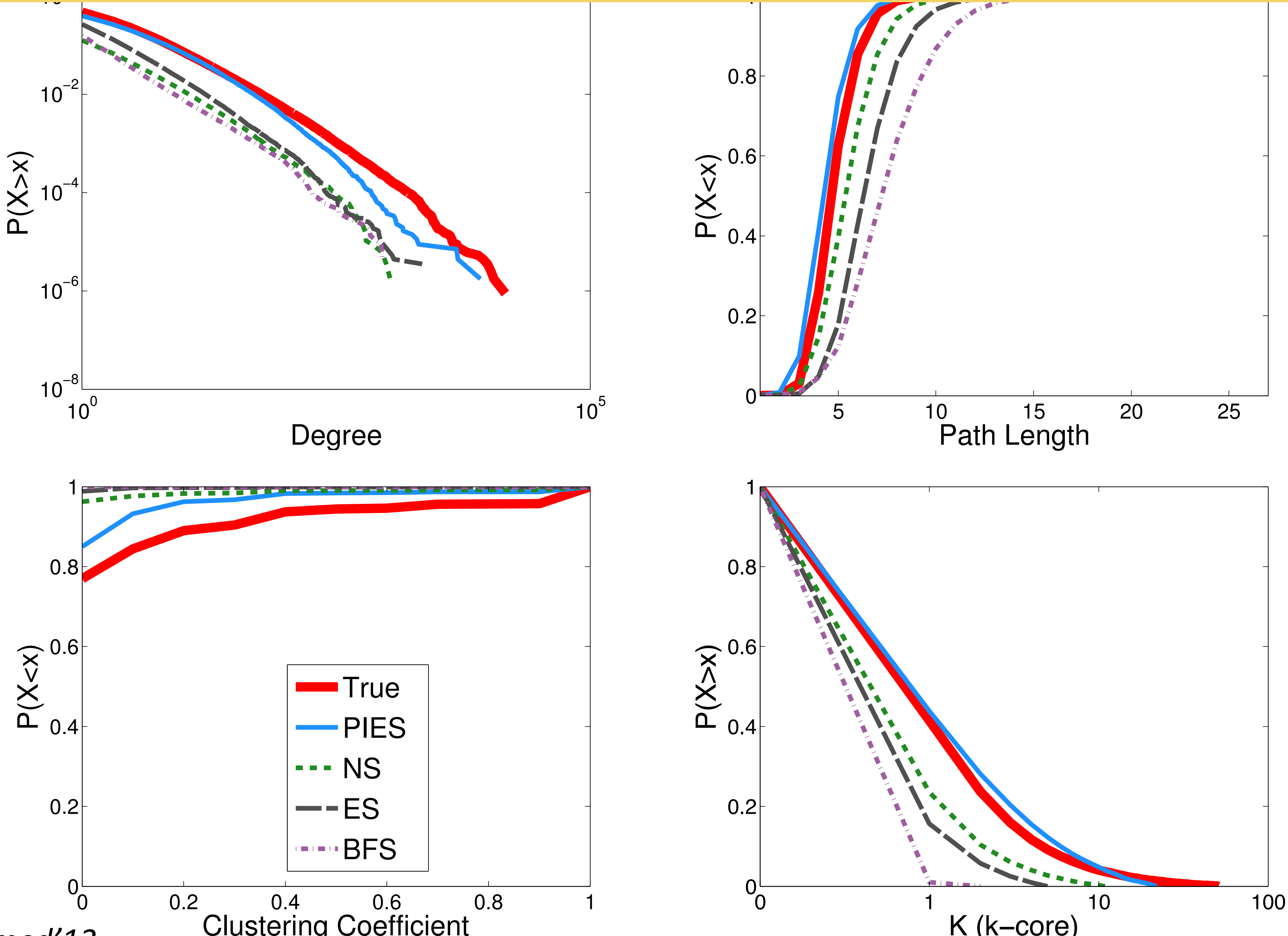
Preserving Max K-core number k_{max}

- Max K-core number k_{max}
  - Largest subgraph in the network with min degree k_{max}
- *Sample size = 20% /Nodes*

Graph	Real max core no.	ES-i	NS	ES	FFS
HepPH	30	23*	8	2	4
CondMAT	25	20*	7	2	6
Twitter	18	18*	5	2	3
Facebook	16	14*	4	2	3
Flickr	406	406*	83	21	7
LiveJournal	372	372*	84	6	7
Email-UNIV	47	46*	15	3	7

Partially Induced Edge Sampling (PIES) performs better than other methods



Ahmed'13

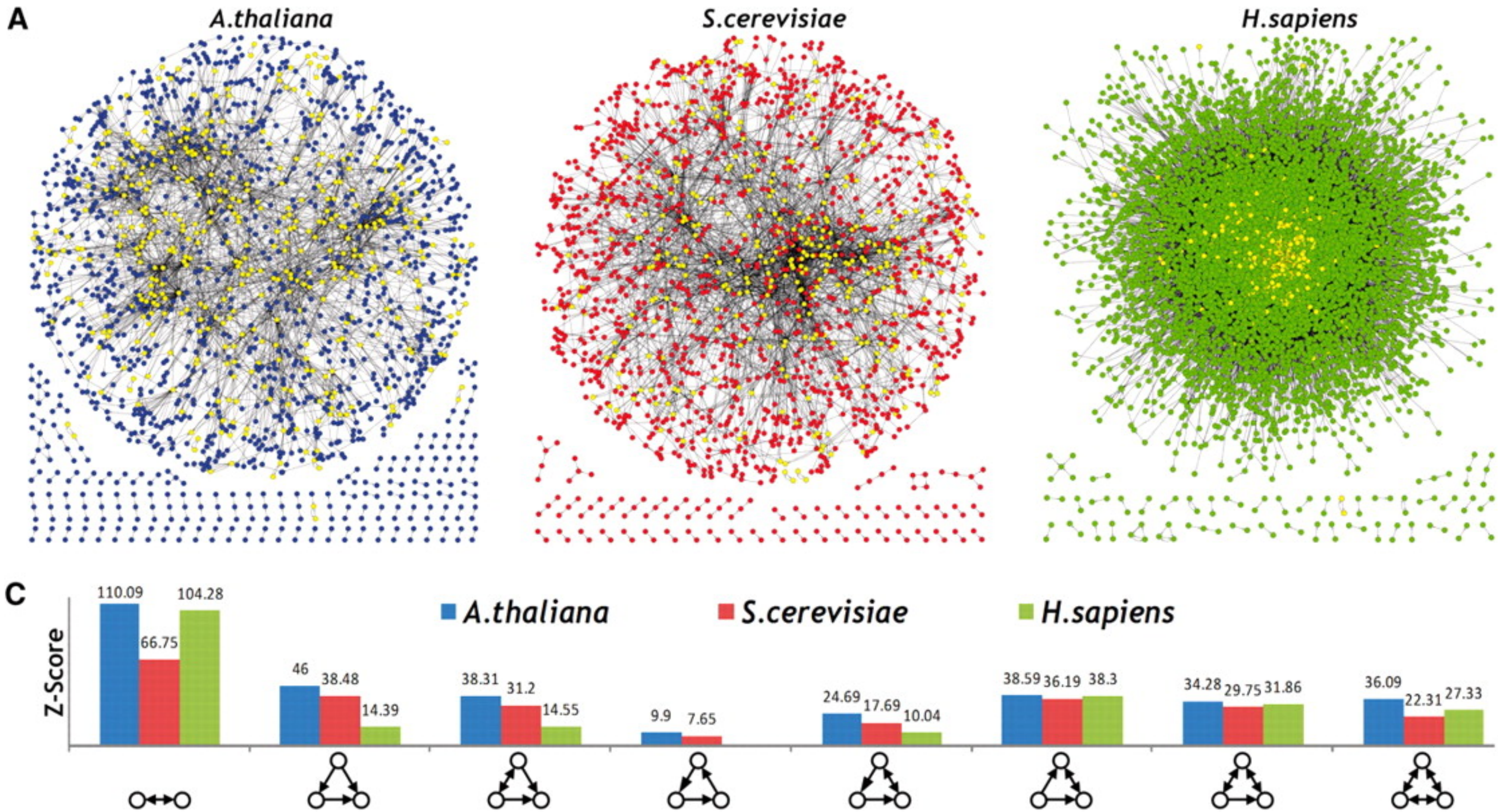
More conclusions …

- Sampling from the stream in one pass is a hard task
  - Exploration methods (Breadth-First) generally don't perform well
    - Solution: Perform more than one sequential pass over the stream
  - Edge-based methods generally perform well
    - **But sometimes** fail to preserve clustering coefficient
- Stream sampling perform better for sparse graphs

TASK 3

Local Sub-structure Sampling

Differentiating species via network analysis of protein-protein interactions



http://bioinformatics.oxfordjournals.org/content/27/2/245/F1.expansion.html

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Task 3 (Sampling sub-structures from networks)

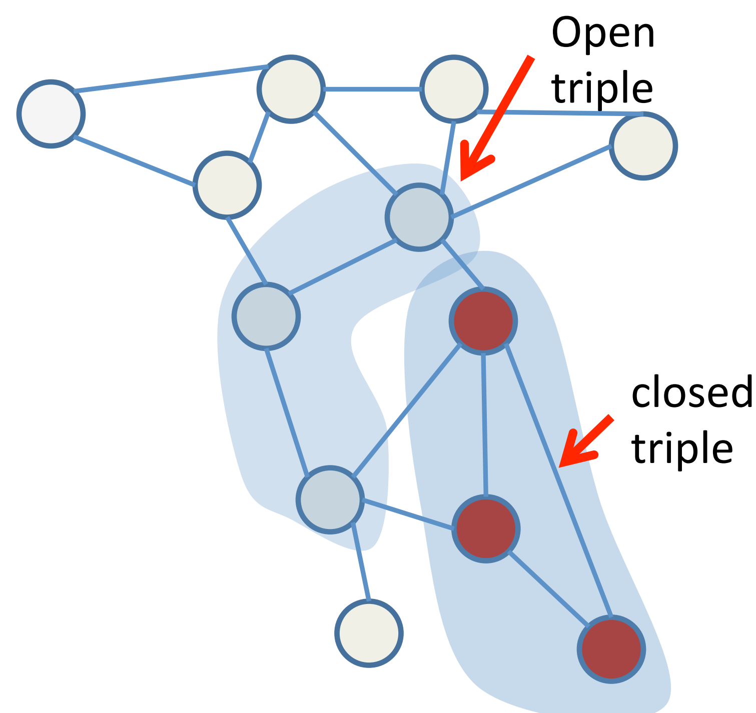
- In this case, our objective is to sample small substructure of interest
  - Sampling graphlets (Bhuiyan et al., 2012)
    - Is used for build graphlet degree distribution which characterize biological networks
  - Sampling triangles and triples (Rahman et al., 2013, Buriol et al., 2006)
    - Is used for estimating triangle count
  - Sampling network motifs (Kashtan et al., 2004, Wernicke 2006)
  - Sampling frequent patterns (Hasan et al. 2009)

Triple sampling from a network: Motivation

- A triple, (u,v,w) at a vertex, v is a path of length two for which v is the center vertex.
- A Triple can be closed (triangle), or open (wedge)

$$triple\text{-}cnt = \sum_{v \in V} \binom{d(v)}{2}$$

- It is useful for approximating triangle counting and transitivity



- T is a set of **uniformly** sampled triples, and $C \subseteq T$, is the set of closed triples
- Approximate transitivity is $\sigma = |C| / |T|$
- Approximate triangle count in a network is: $\frac{\sigma}{3} \cdot triple\text{-}count$

Induced k-Subgraph Sampling: motivation

- Network motifs are induced subgraphs that occur in the network far more often than in randomized networks with identical degree distribution

- To identify network motif, we first construct a set of random networks (typically few hundreds) with identical degree distributions.

- If the concentration of some subgraph in the given network is *significantly* higher than the concentration of that subgraph in the random networks, those subgraphs are called *network motif*

- Concentration of a size-k subgraph $S_i^{(k)}$ is defined as: $$C_i^{(k)}(G) = \frac{f_i^{(k)}(G)}{\sum_{j:\ \mathrm{size}(j)=k} f_j^{(k)}(G)}$$

- Exact counting of k-subgraphs are costly, so sampling methods are used to approximate k-subgraph concentrations

Estimate node/edge properties in original network

Sample representative subgraph/subnetwork

Estimate frequency of subgraph patterns

Data Access Assumption

	Task 1	Task 2	Task 3
Full Access	✓	✓	✓
Restricted Access	✓	✓	
Data Stream Access	✓	✓	

Sampling Objective

Sampling methodology

Triple sampling with full access

- Take a vertex v uniformly, choose two of its neighbors u , and w ; return the triple (u, v, w)
- This **does not** yield uniform sampling, as the number of triples centered to a vertex is non-uniform,

$$\mathrm{P}\{\text{triple } (u, v, w) \text{ is sampled}\} = \frac{1}{n \cdot \binom{d(v)}{2}}$$

- For triangle counting from a set of sampled triples (say, T) , we can apply the same un-biasing trick that we applied for nodal characteristics estimation,

$$TC = \frac{\textit{triple-cnt}}{3 \cdot W} \times \sum_{t \in T} w_t \cdot 1_{\{t \text{ is closed}\}}$$

here w_t is the probability of selecting a triple, and $W = \sum_{t \in T} w_t$

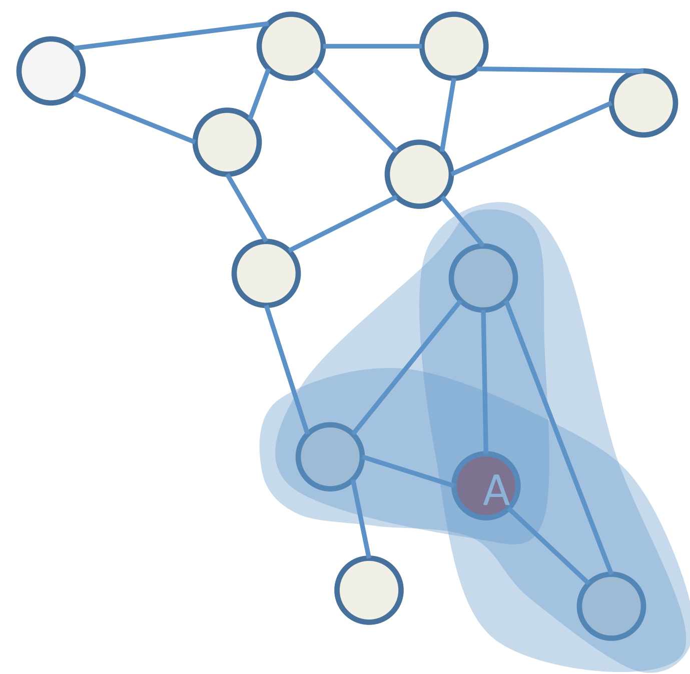
Uniform Triple sampling with full access [Schank '05]

- Method
  - Select a node v in proportion to the number of triples that are centered at v, which is equal to

$$\frac{d(u)(d(u)-1)}{2}$$

  - Return one of the triple centered at v uniformly
  - For the first step, we need to know the degree of all the vertices
- Triangle count estimate is easy, we just need to use the formula

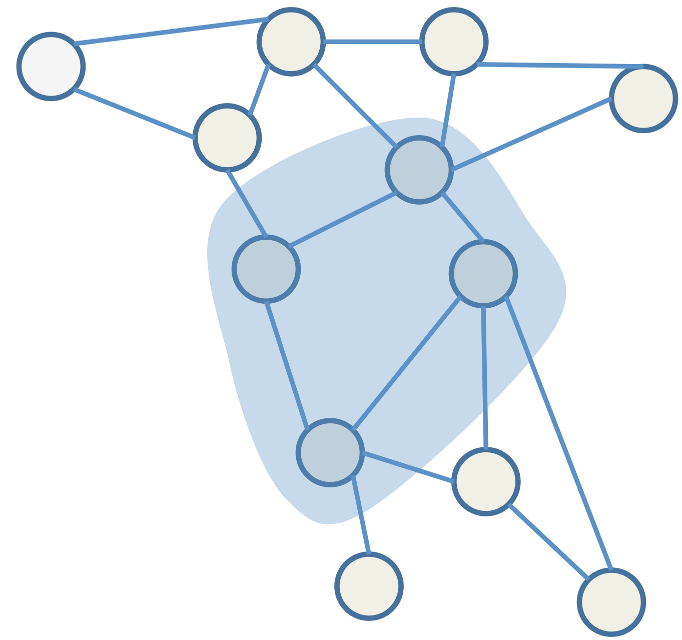
$$TC = \frac{triple\text{-}cnt}{3 \cdot |T|} \times \sum_{t \in T} 1_{\{t \text{ is closed}\}}$$



Node A has degree 3, it has 3 triples centered around it

Sampling of subgraphs of size k [Kashtan '04]

- Method
    1. Select an edge uniformly
    2. Populate Neighborhood
    3. Choose one neighbor uniformly
    4. If size ≠ k , goto 2 else return the pattern



k=4

Probability of generating this pattern (in this edge order) :

$$= \frac{1}{m} \times$$
$$= \frac{1}{m} \times \frac{1}{7}$$
$$= \frac{1}{m} \times \frac{1}{7} \times \frac{1}{7}$$
$$= \frac{1}{49m}$$

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Sampling of subgraphs of size k Kash

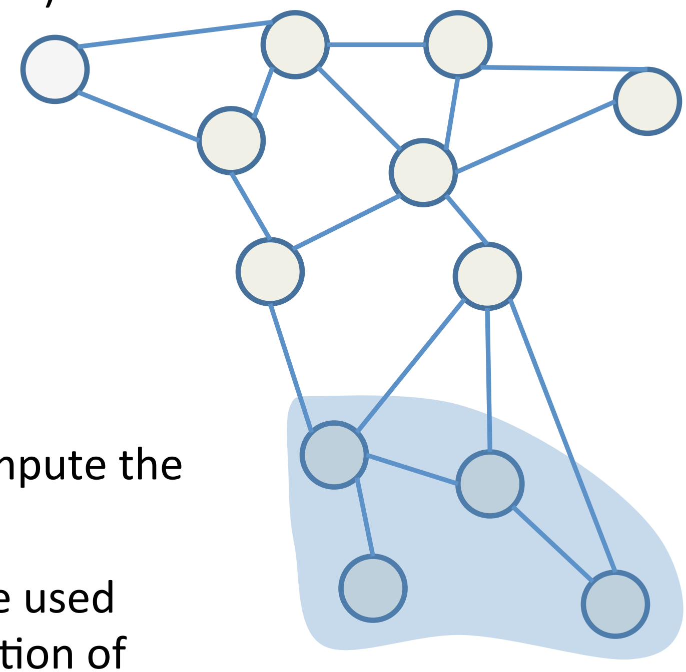
Probability of generating this pattern (in this edge order) :

$$= \frac{1}{m} \times$$

$$= \frac{1}{m} \times \frac{1}{3}$$

$$= \frac{1}{m} \times \frac{1}{3} \times \frac{1}{3}$$

$$= \frac{1}{9m}$$



k=4

- Sampling probability is not uniform, but we can compute the probability
- We can apply the same unbiasing trick that we have used before to obtain uniform estimate of the concentration of some subgraph of size k
- Assume, we take B samples of size-k subgraph, Then the concentration of some subgraph type s_i is:,

$$\frac{\sum_{j=1}^{B} w_j \cdot 1_{\{j\cdot type = s_i\}}}{W}$$ where $w_j = \frac{1}{P_j}$, and $W = \sum_{j=1}^{B} w_j$

Estimate node/edge properties in original network

Sample representative subgraph/subnetwork

Estimate frequency of subgraph patterns

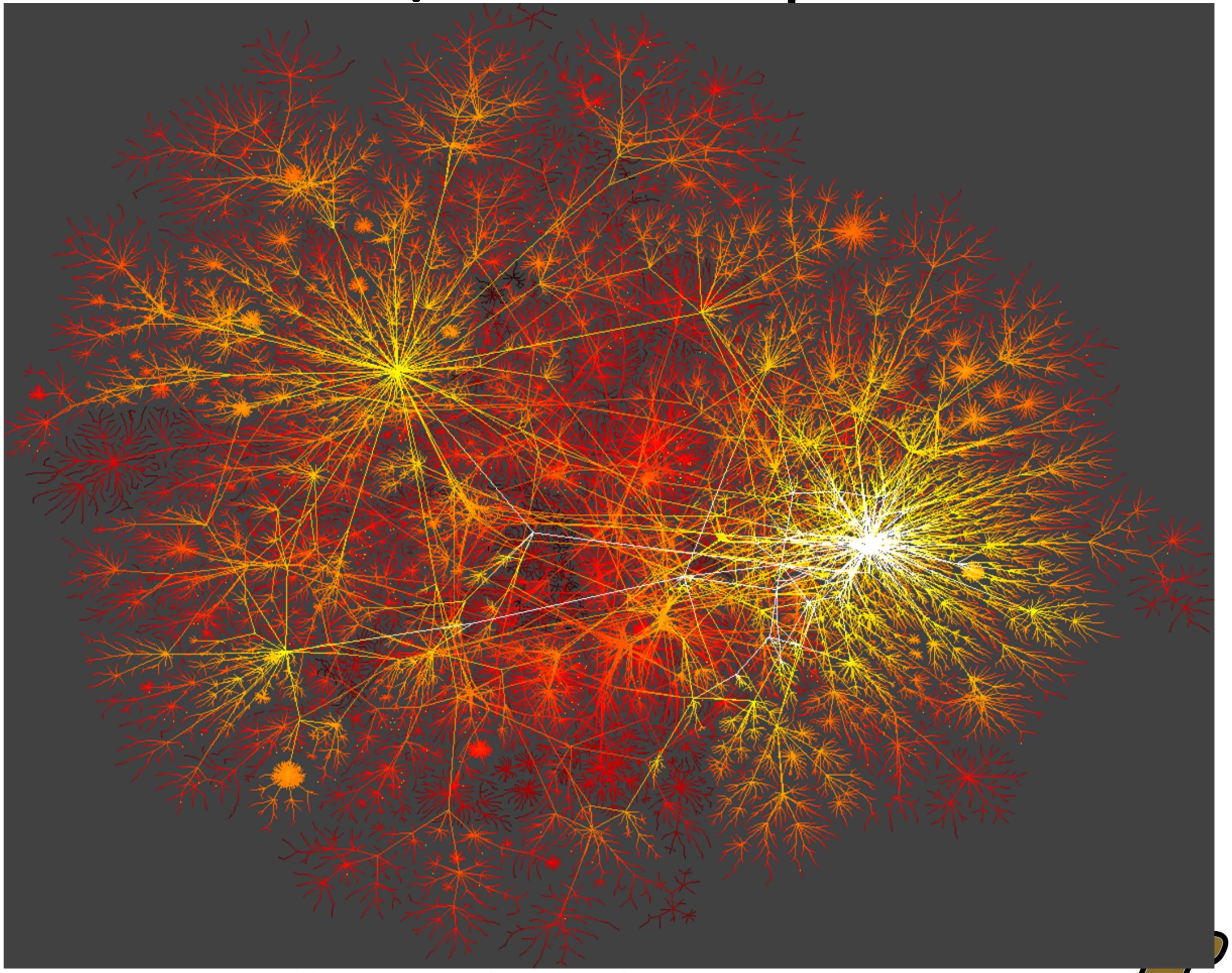
Data Access Assumption

	Task 1	Task 2	Task 3
Full Access	✓	✓	✓
Restricted Access	✓	✓	✓
Data Stream Access	✓	✓	

Sampling Objective

Sampling methodology

Sampling to detect internet attacks and/or web spam

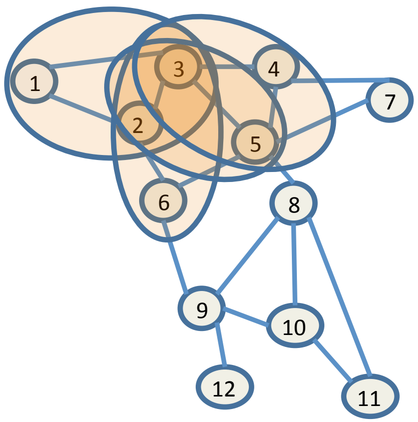


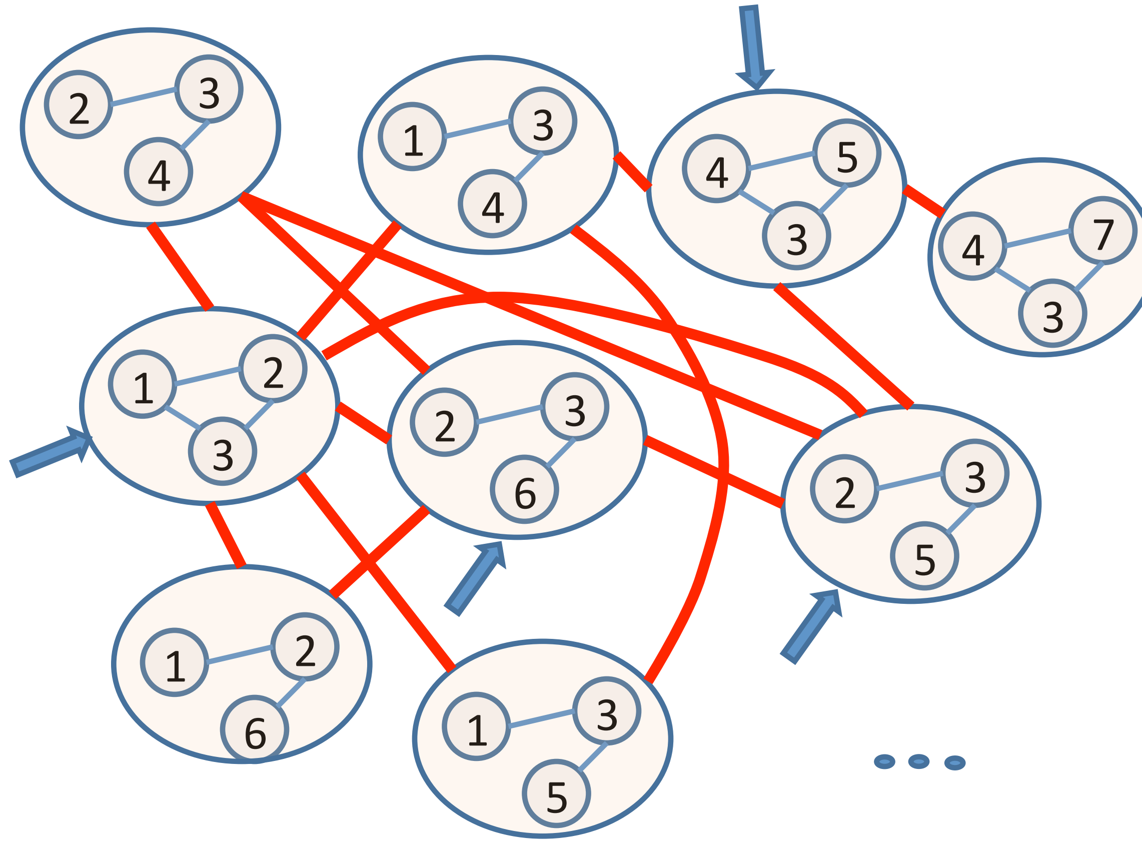
http://www3.nd.edu/~networks/Image%20Gallery/gallery.htm

Triple sampling by exploration

- Perform a random walk over the triple space
  - Given a seed node, form a triple from its neighborhood information
  - Define a neighborhood in the triple space that can be instantiated online using local information
  - Choose the next triple from the neighborhood
- The stationary distribution of the walk is proportional to the number of neighbors of a triple in the sampling space

Neighborhood





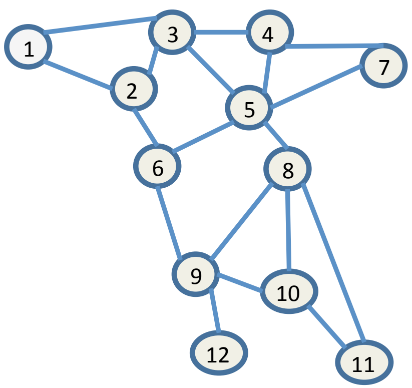
Two neighboring triples share two vertices among them, entire neighborhood graph is not shown

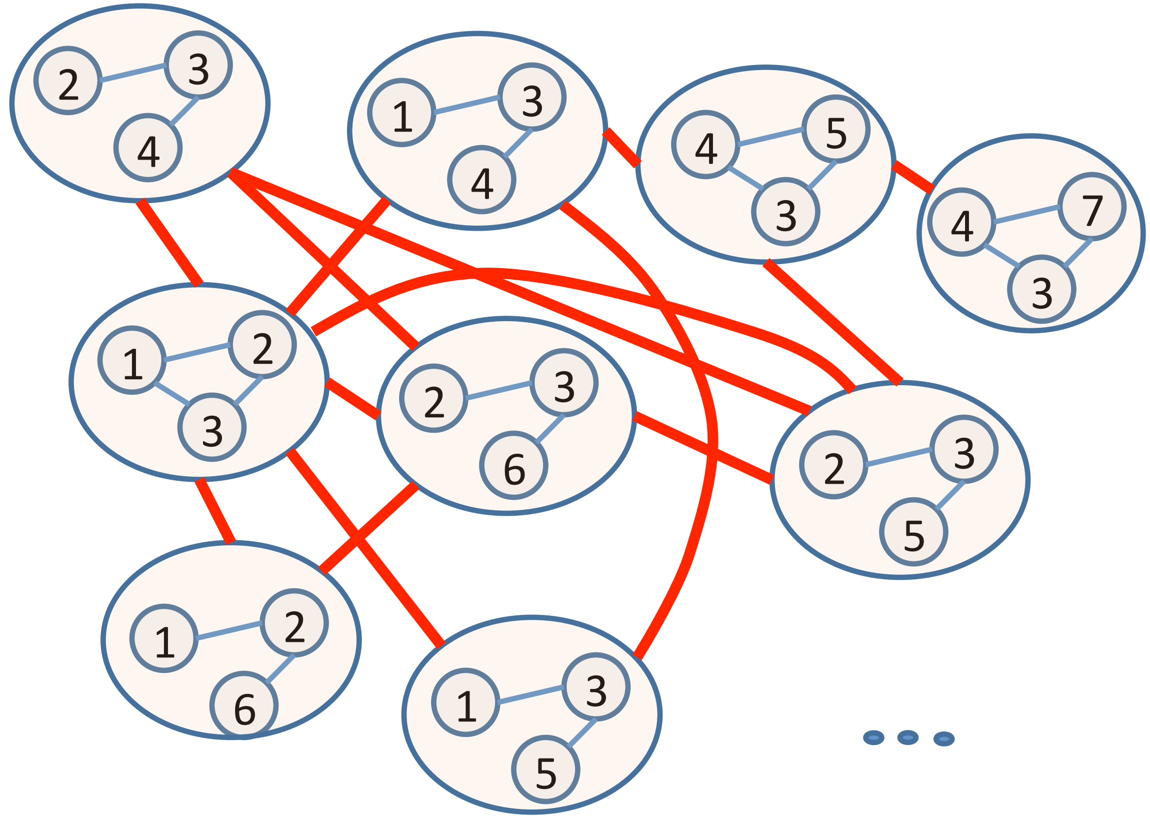
Triple sampling by exploration based solution for restricted access

- If we want to obtain unbiased estimate of the concentration of triangle (transitivity), we can use the same un-biasing strategy as before:
  - The concentration of triangle is: ,

$$\frac{\sum_{j=1}^{B} w_j \cdot 1_{\{j \cdot type=closed\}}}{W}, \text{ here, W=} \sum_{j=1}^{B} w_j \text{ and } w_j = 1/d(j)$$

Neighborhood





Degree of the triple (1, 2, 3) is 6 as can be seen in the above graph, so while unbiasing,

$$w_{(1,2,3)} = \frac{1}{6}$$

Another exploration-based triple sampling that uses MH algorithm

- MH algorithm uses simple random walk as proposal distribution
- Then is uses the MH correction (accept/reject) so that the target distribution is uniform over all the triples
- Like before, if triple T_i is currently visiting state, and the triple T_j is chosen by the proposal move, then this move is accepted with probability $\min\left\{1, \frac{d(i)}{d(j)}\right\}$
- MH algorithm thus confirm uniform sampling, so the transitivity can be easily computed as $\frac{1}{|T|}\sum_{k=1}^{|T|} 1_{\{T_k \text{ is closed}\}}$

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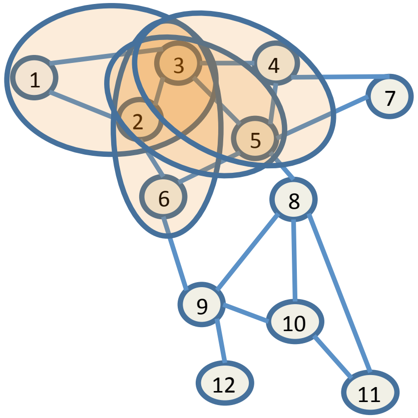
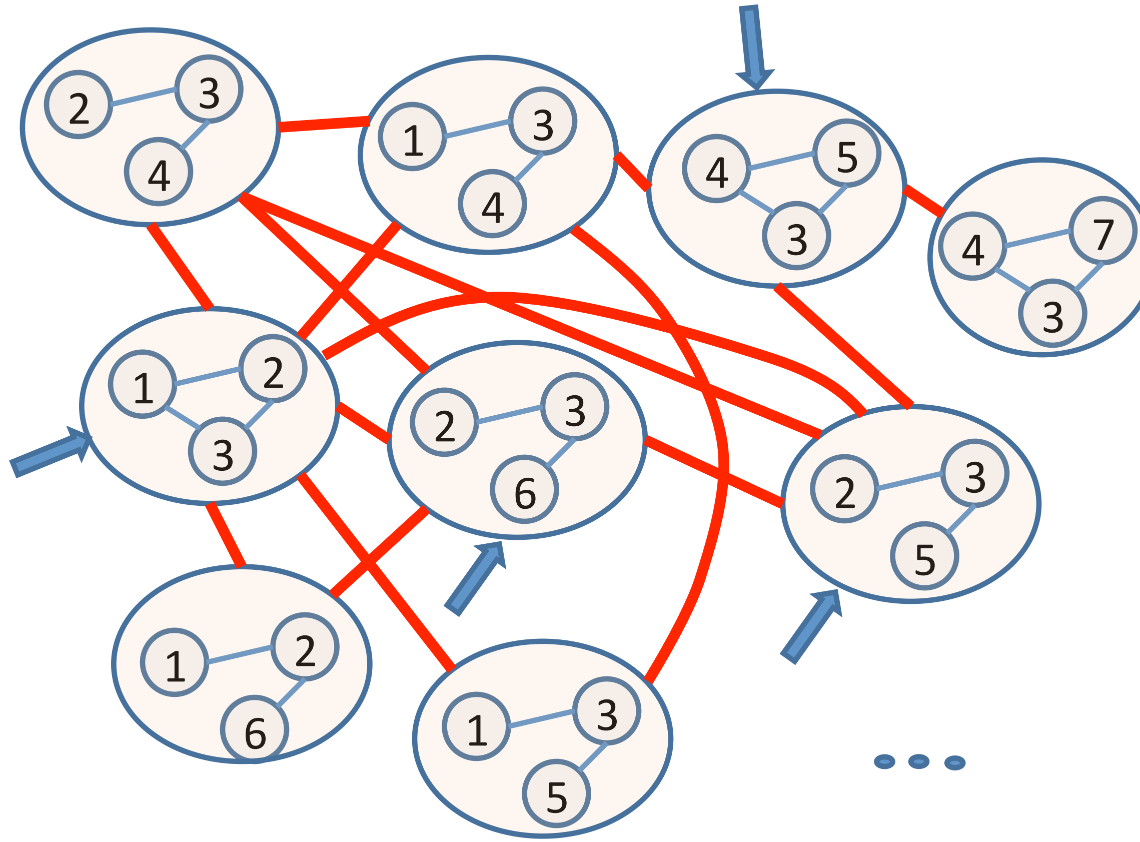
Neighborhood





- For uniform sampling, Every move from triple T_i to triple T_j is accepted with probability $d(T_i)/d(T_j)$
- If $T_i = (1, 2, 3)$ and $T_j = (1,3,4)$, move from T_i to T_j is accepted with probability $\max\{1, 6/4\} = 1$, but a move from T_j to T_i is accepted with probability, $\max\{1, 4/6\} = 4/6$

Sampling subgraphs of size k using exploration [Bhuiyan '12]

- Both random walk and M-H algorithm can also be used for sampling subgraph of size k
- As we did in triangle sampling, we simply perform a random walk on the space of all subgraphs of size-k
- We also define an appropriate neighborhood
  - For example, we can assume that two k-subgraphs are neighbors, if they share $k-1$ vertices
- This idea has recently been used in GUISE algorithm, which uniformly sampled all subgraphs of size 3, 4, and 5. It used M-H methods
  - Motivation of GUISE was to build a fingerprint for graphs that can be used for characterizing networks from different domains.

Estimate node/edge properties in original network

Sample representative subgraph/subnetwork

Estimate frequency of subgraph patterns

Data Access Assumption

	Task 1	Task 2	Task 3
Full Access	✓	✓	✓
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Data Stream Access	✓	✓	✓

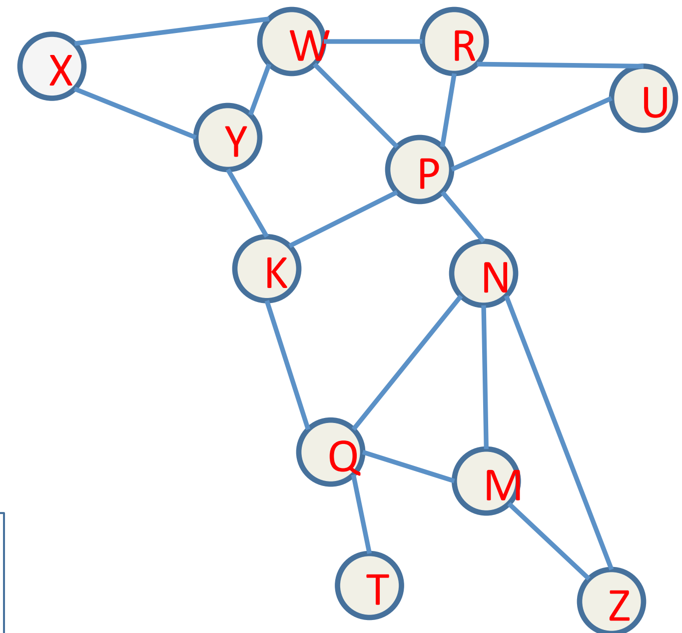
Sampling Objective

Sampling methodology

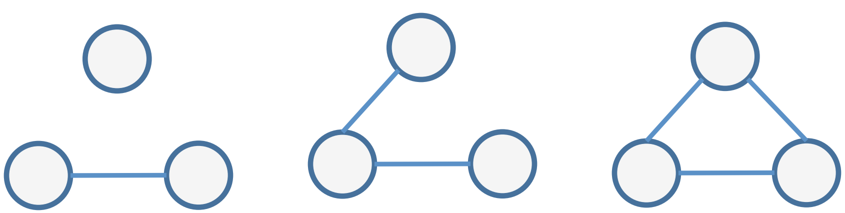
Triple Sampling from edge stream

- Sampling subgraphs using streaming method is not easy, existing works only covered subgraphs with three and four vertices
- Large number of works exist that aim to sample triples for approximating triangle counting from stream data
- For graph steam, there are two scenarios:
  - Arbitrary edge stream: Stream of the edges appear in arbitrary order
  - Incident edge stream: Stream of the edges incident to some vertices come together, whereas the ordering of vertices is arbitrary

3-pass triangle counting (arbitrary edge stream) [Buriol '06]



- First Pass: Count edges = 18
- Second Pass: Uniformly sample an edge (K, P) and a vertex (M)
- 3[rd] Pass: Look for existence of (K, M) and (M, P) in the stream, if exist set $\beta=1$, else $\beta=0$



Set size T_1 | Set size T_2 | Set size T_3

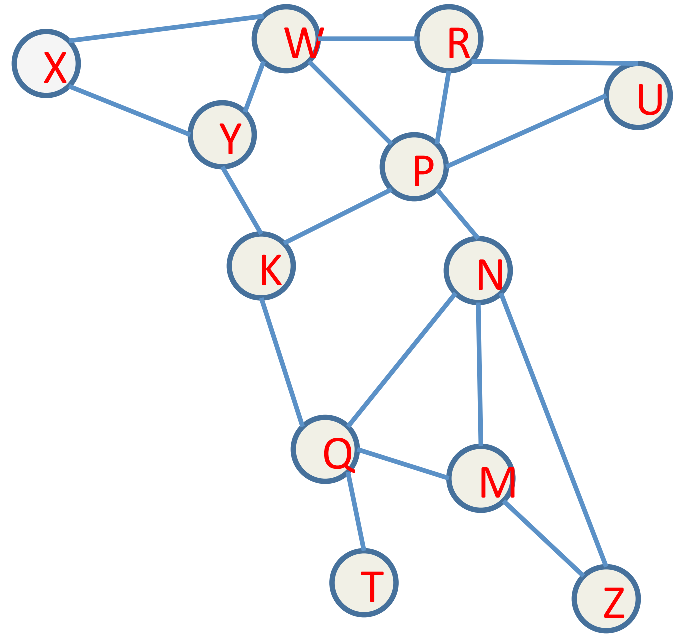
$$m(n-2) = T_1 + 2T_2 + 3T_3$$

$$E[\beta] = 3T_3 / (T_1 + 2T_2 + 3T_3) = 3T_3 / m(n-2)$$

$$T_3 = E[\beta] \cdot m(n-2)/3$$

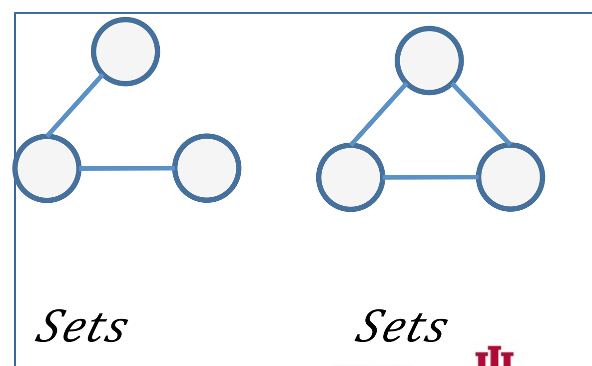
3-pass triangle counting (incident edge stream) [Buriol '06]

- First Pass: Count number of triples, $p = \sum_v \binom{d(v)}{2}$
- Second Pass: Uniformly sample a triple (K, P, N) centered at P
- 3rd Pass: Look for existence of (K, N) edge in the stream, if exist set $\beta = 1$, else $\beta = 0$



$$p = \sum_v \binom{d(v)}{2} = T_2 + 3T_3$$
$$E[\beta] = 3T_3 / (T_2 + 3T_3) = 3T_3 / p$$

$$T_3 = E[\beta] \times p/3$$



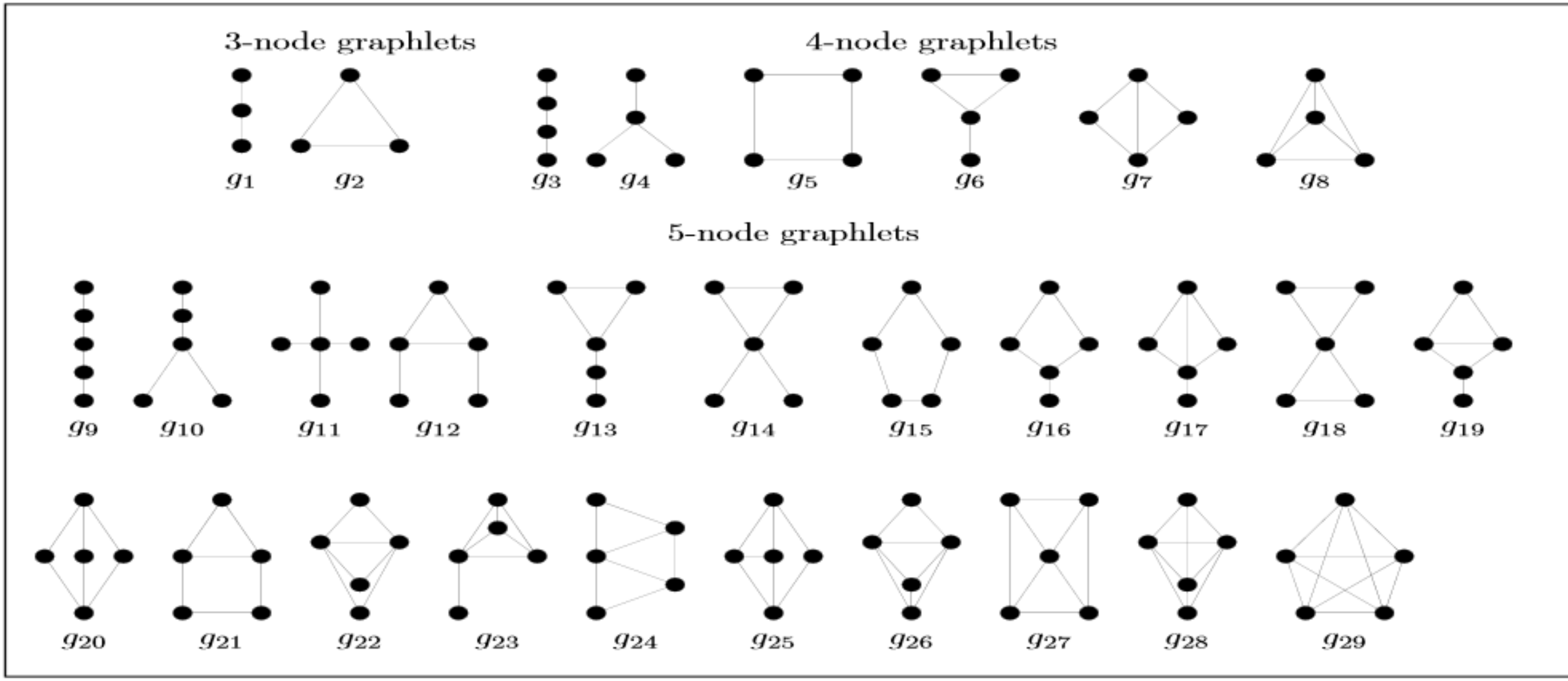
Sets ize T_2

Sets ize T_3

RESULTS

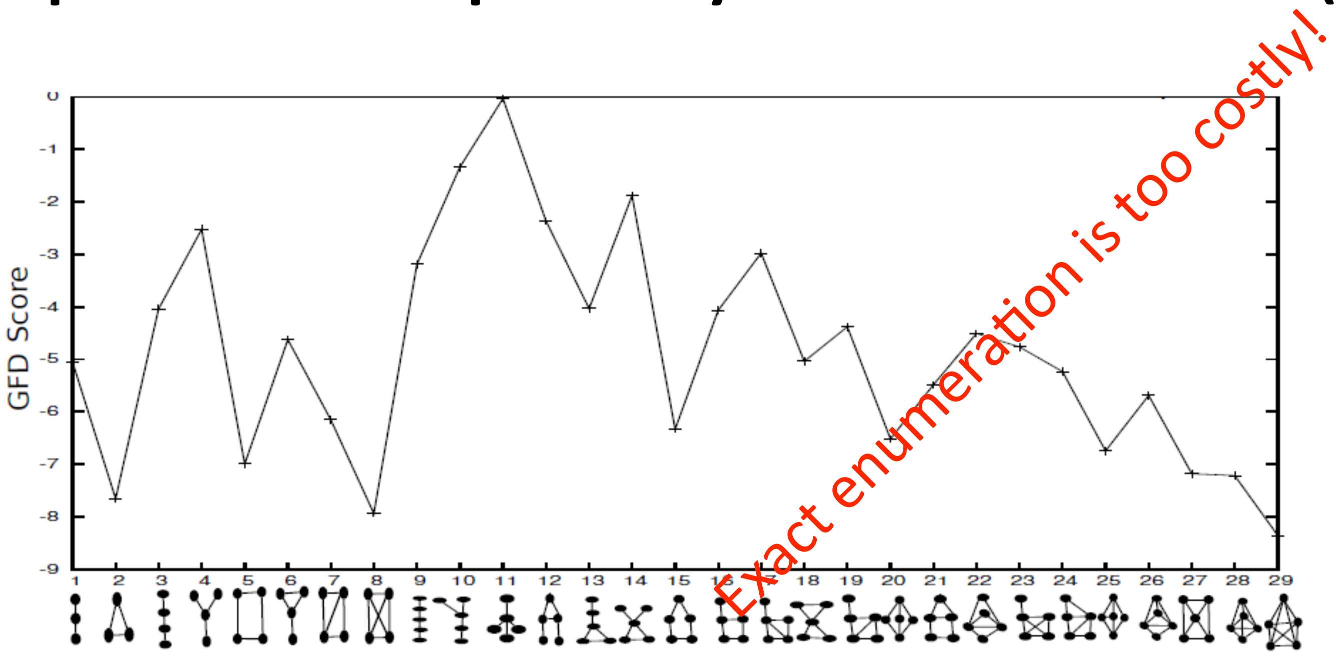
What matters. Where it matters.

Graphlet sampling [Bhuiyan ’12]



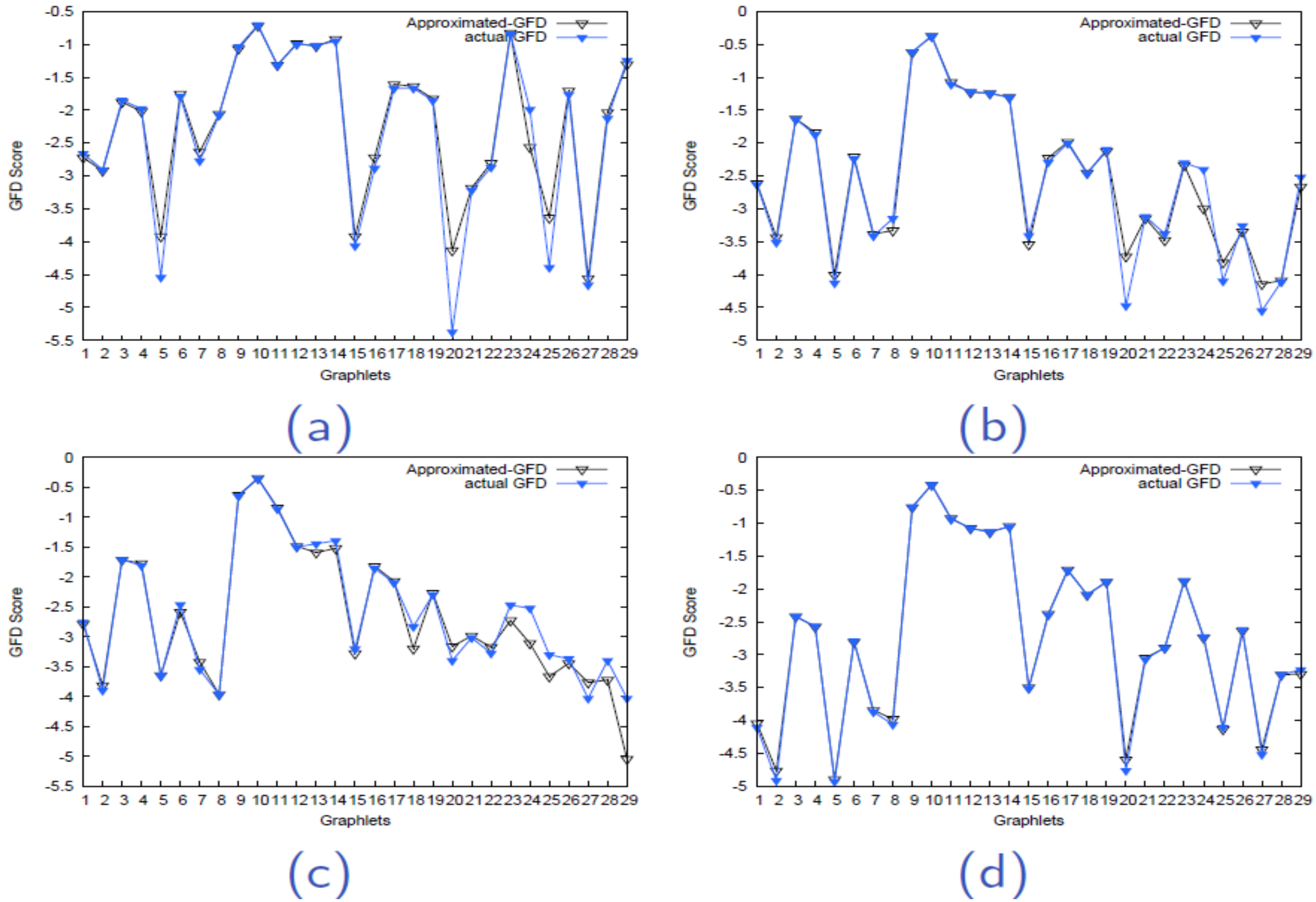
- Given a large graph, we want to count the occurrences of each of the above graphets
- Using the graphlet counts, we want to build a frequency histogram (GFD) to characterize the graph

Graphlet Frequency Distribution (GFD)



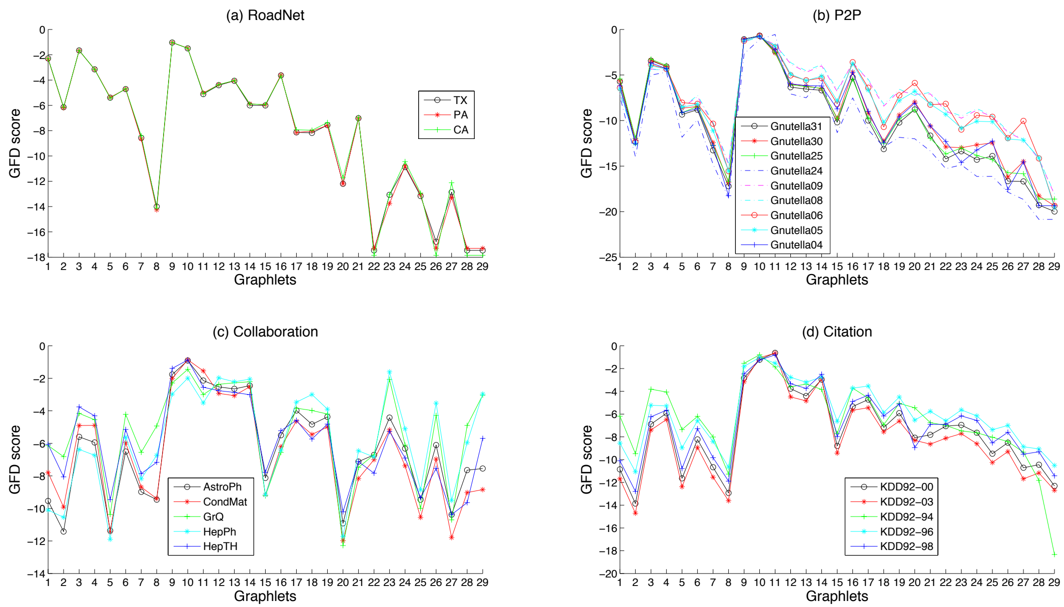
- Approximate the frequency of each graphlet using their relative frequency by random walk sampling
- Use logarithm of normalized frequency to plot GFD

Exact Vs App GFD



Comparison with Actual and Approximate GFD for
(a) ca-GrQc (b) ca-Hepth (c) yeast (d) Jazz

Use of GFD [Rahman '13]



- GFD can represent a group of graphs constructed using same mechanism.
- We used GFD in agglomerative hierarchical clustering which produced good quality (purity close to 90%) cluster.

Real Graph-Groups

		P2P	Collaboration	RoadNet	Citation
Graph cluster	P2P	9	0	0	0
	Collaboration	0	5	0	2
	RoadNet	0	0	3	0
	Citation	0	0	0	3

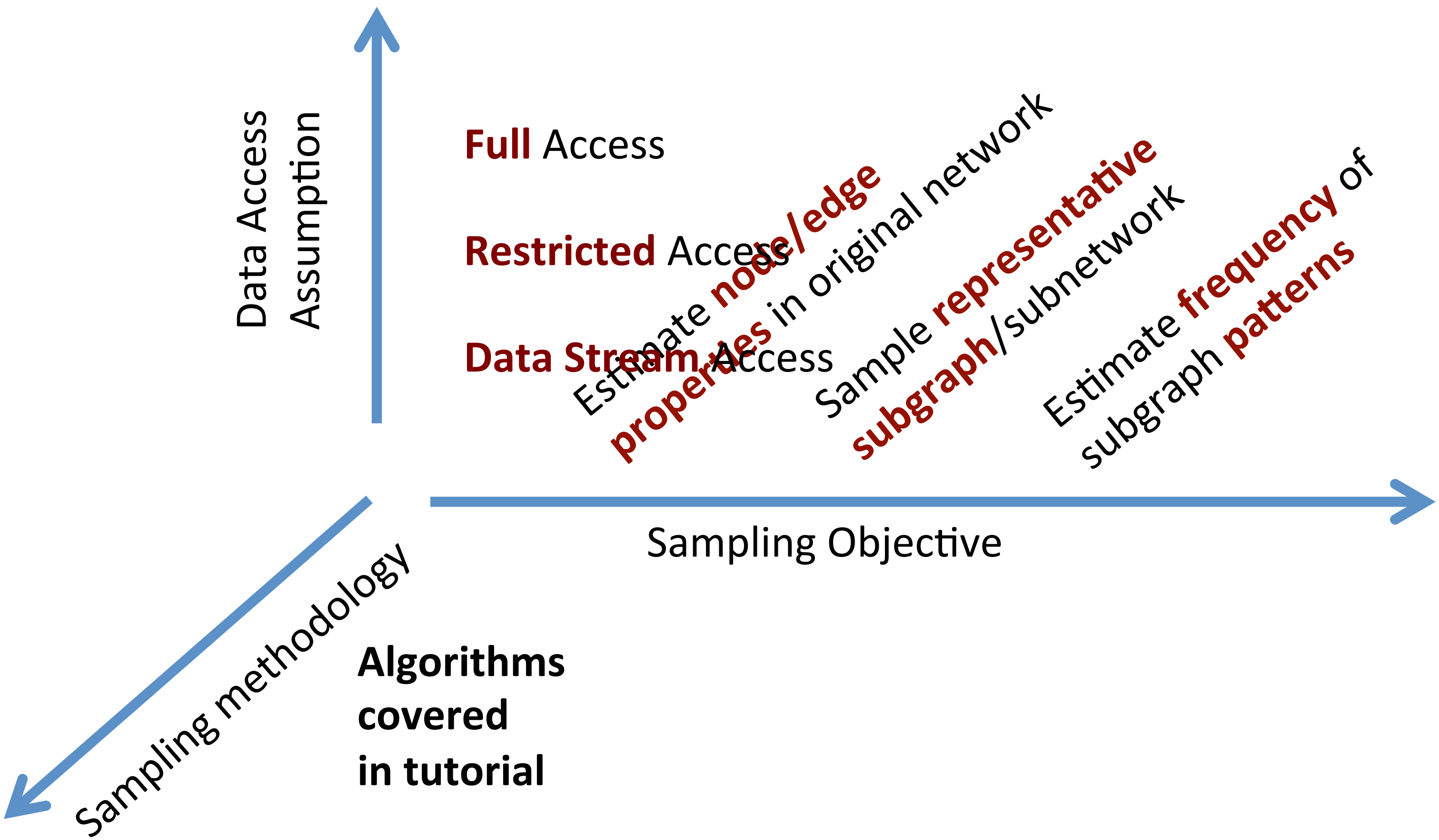
Result of agglomerative hierarchical graph-clustering (first 18 dimensions of GFD used).

$$Purity = \frac{9+5+3+3}{22} = 0.91$$

IUPUI

at matters. Where it matters.

Conclusion



Data Access Assumption
Full Access
Restricted Access
Data Stream Access
Estimate node/edge properties in original network
Sample representative subgraph/subnetwork
Estimate frequency of subgraph patterns
Sampling Objective
Sampling methodology
Algorithms covered in tutorial

Concluding remarks

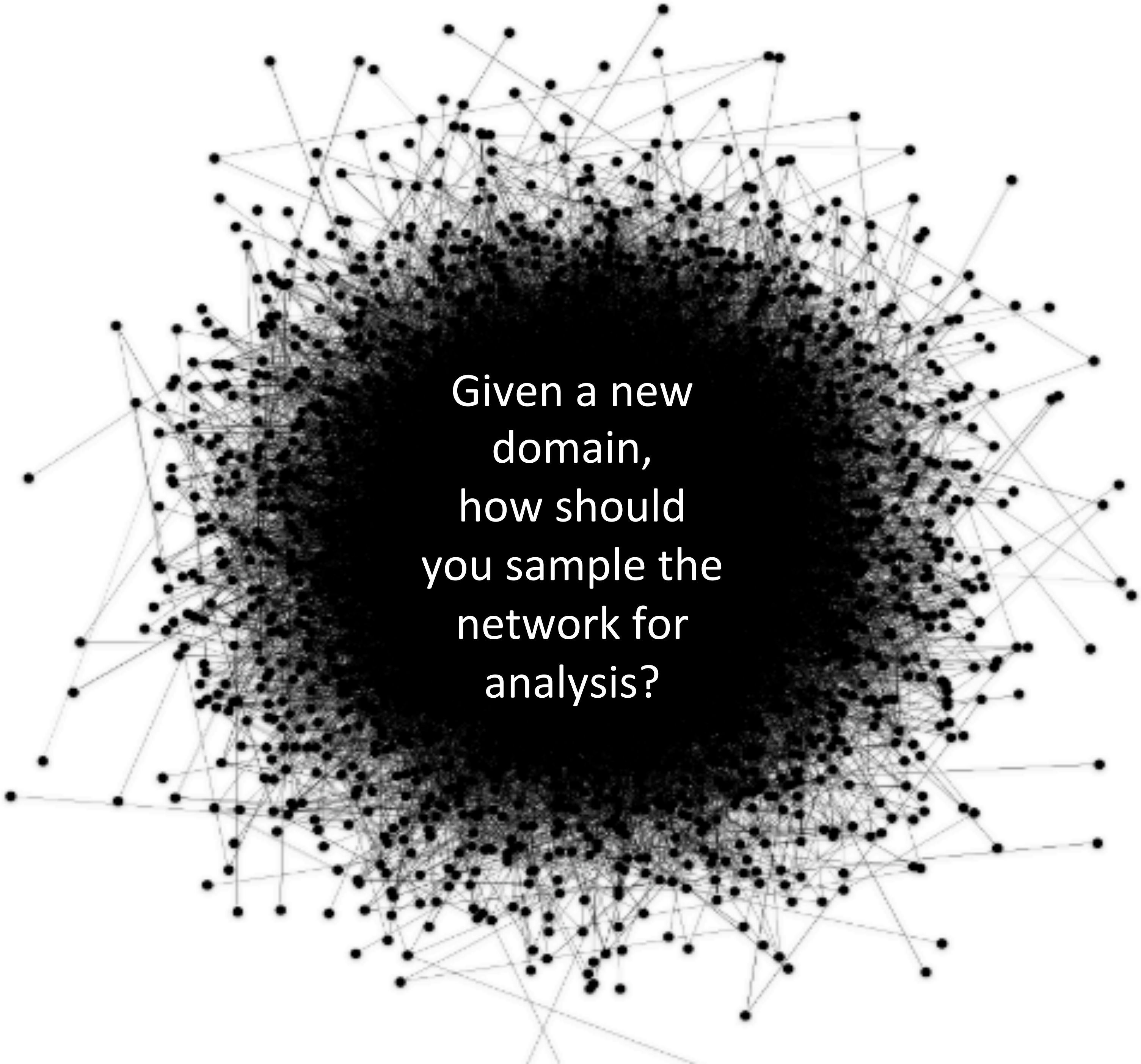
- Generally for many tasks, you will need uniform sampling of “objects” from the network (eg. Task 1 and Task 3 in our slides)
  - Uniform sampling with full access is generally easier for node or edge sampling,
  - sampling higher order structure is still hard because the sampling space is not instantly realizable without brute-force enumeration.
  - For uniform sampling under access restriction, both M-H, and SRW-weighted (with bias correction) works; both guaranty uniformity by theory, but SRW-weighted provides marginally better empirical sampling accuracy.

Concluding remarks

- For sampling a representative sub-networks (Task 2), unbiased sampling is typically NOT a good choice. From empirical observation, biased sampling helps obtain better representative structure
  - It is difficult to select a subgraph that preserves ALL properties, so sampling mechanism should focus on properties of interest
  - Theory has generally focused on kind of nodes that are sampled. More works are needed to show the connection between types of nodes sampled and resulting higher order topological structure

Concluding remarks (cont.)

- In present days, streaming is becoming more natural data access mechanism for graphs. So, currently it is an active area of research
  - It presents unique challenges to sample topology in an unbiased way, because local views of stream do not necessarily reflect connectivity.
  - Existing works have solved some isolated problems exactly (eg. triangle sampling, pagerank computation), and some other empirically (eg. representative sub-network)


Given a new
domain,
how should
you sample the
network for
analysis?

Define your task

↓

Select sampling objective

↓

Consider data access restrictions

↓

Choose sampling method

↓

Evaluate sampling quality

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Thank you!

Questions?