

Fast Reliability Search in Uncertain Graphs

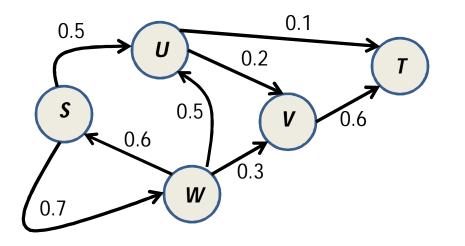
Arijit Khan, Francesco Bonchi, Aristides Gionis, Francesco Gullo

Systems Group, ETH Zurich Yahoo Labs, Spain Aalto University, Finland



1

Uncertain Graphs



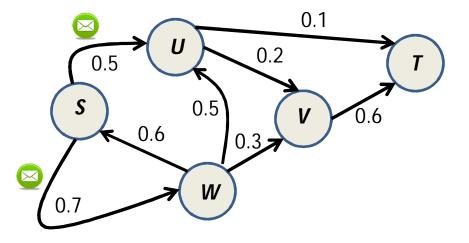
Uncertain Graph

- Social Network
- Traffic Network
- Ad-hoc Mobile Network
- Protein-interaction Network



Motivation

- Mobile Ad-hoc Network: find the set of sink nodes where a source node can deliver a packet with high probability
- Traffic Network: find a set of target locations reachable from a source location with high probability
- Social Network: find a set of users who could be influenced with high probability by a target user

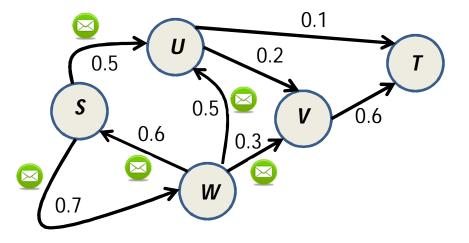


Packet Delivery Probability in Mobile Ad-hoc Network



Motivation

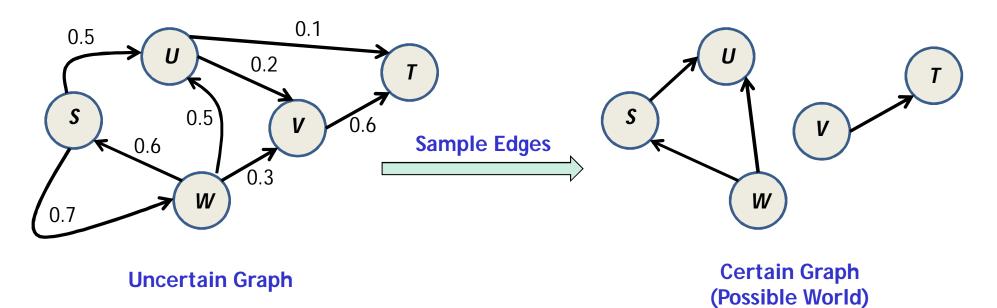
- Mobile Ad-hoc Network: find the set of sink nodes where a source node can deliver a packet with high probability
- Traffic Network: find a set of target locations reachable from a source location with high probability
- Social Network: find a set of users who could be influenced with high probability by a target user



Packet Delivery Probability in Mobile Ad-hoc Network

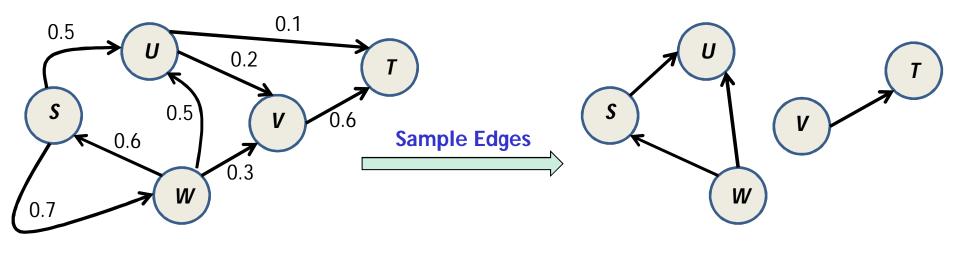


Reliability in Uncertain Graphs





Reliability in Uncertain Graphs



Uncertain Graph

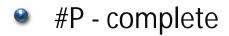
Certain Graph (Possible World)

$$\Pr(G) = \prod_{a \in A_G} p(a) \prod_{a \in A \setminus A_G} (1 - p(a))$$



Reliability Search in Uncertain Graphs

Given an uncertain graph G, a probability threshold $\eta \in (0, 1)$, and a source node S in G, find all nodes in G that are reachable from S with probability greater than or equal to threshold η

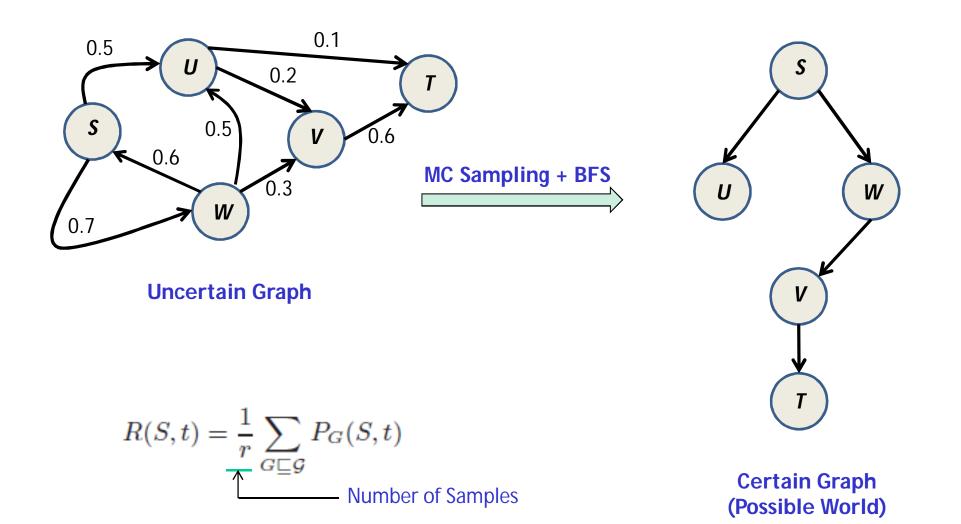




Related Work

- Two-terminal reliability
- All-terminal reliability
- K-terminal reliability
- Monte-Carlo (MC) sampling
- Distance-constraint reliability RHT sampling (Jin et. al., VLDB 2011)

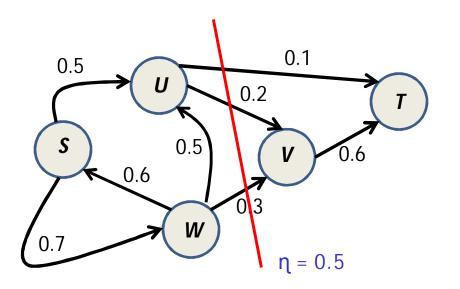
Baseline - MC Simulation + BFS





Can We Be More Efficient?

Siven a source node S and a probability threshold $\eta \in (0, 1)$, can we quickly determine the nodes that are certainly not reachable from S with probability greater than or equal to η

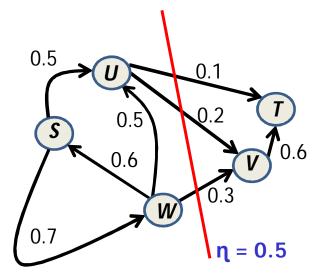


- Indexing (offline)
- Filtering + Verification (Online)

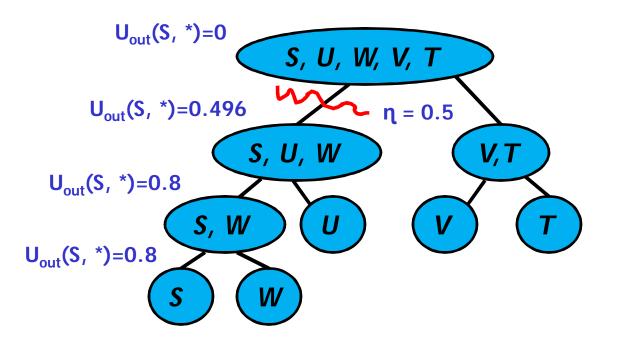
Uncertain Graph



RQ-Tree Index



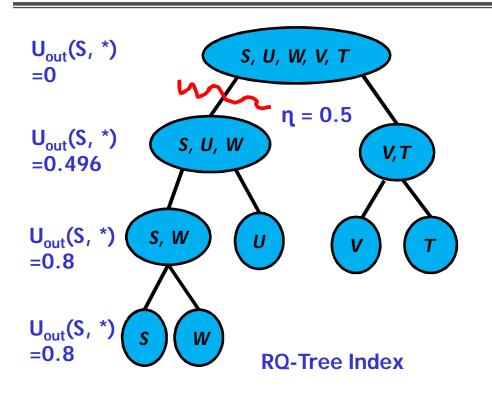
Uncertain Graph



RQ-Tree Index



RQ-Tree: Filtering



Max-Flow Min-Cut Based Upper Bound:

Edge Capacity:

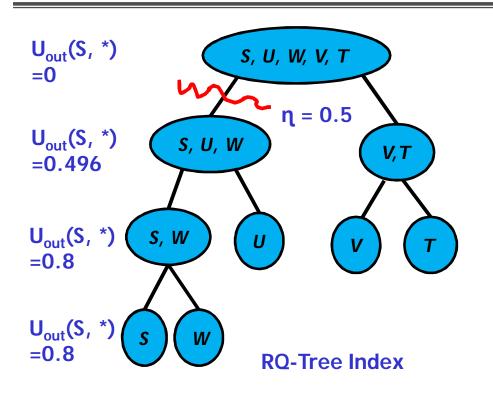
 $c(a) = -\log\left(1 - p(a)\right)$

 Compute Max-Flow f from S to Outside Cluster C

•
$$U_{out}(S, C) = 1 - exp(-f)$$



RQ-Tree: Filtering



Benefits:

- No false negative (recall = 1)
- Computation limited only inside cluster C
- Incremental Max-Flow computation

Max-Flow Min-Cut Based Upper Bound:

• Edge Capacity:

 $c(a) = -\log\left(1 - p(a)\right)$

 Compute Max-Flow f from S to Outside Cluster C

•
$$U_{out}(S, C) = 1 - exp(-f)$$



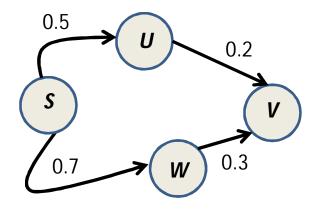
RQ-Tree: Verification

Sampling-based Verification:

- MC-Sample + BFS over the sub-graph formed by the candidate set
- Pros: high precision, high recall
- Cons: verification could still be relatively expensive

Lower-Bound-based Verification:

- Most-Likely-Path
- Pros: precision = 1, high efficiency
- Cons: lower recall



Pr(S-U-V) = 0.5 * 0.2 = 0.10 Pr(S-W-V) = 0.7 * 0.3 = 0.21

Most-Likely-Path: (S-W-V)



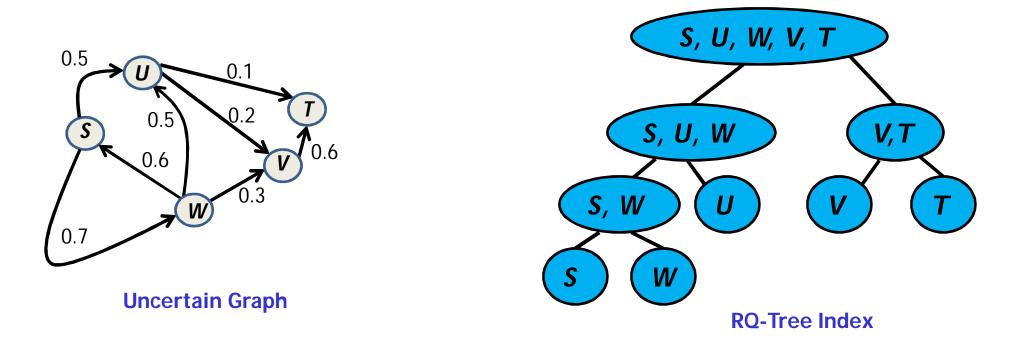
RQ-Tree: Online Complexity

MC Sampling	Recursive Sampling [VLDB '11]	RQ-Tree + MC-Sampling-based Verification [Our Method]	RQ-tree + Lower-Bound-based Verification [Our Method]
O(K(m+n))	$O(n^2d)$	$O\left(\hat{m}\hat{n}+K\left(\hat{m}+\hat{n}\right)\right)$	$O\left(\widehat{m}\widehat{n}\right)$

- K = No of Samples
- m = No of edges
- n = No of nodes
- $\hat{n} = \text{No of nodes in the candidate set}$
- \widehat{m} = No of edges induced by the candidate nodes
- d = Diameter of the graph



RQ-Tree Index Construction



Hierarchical Clustering:

- Minimum-cut balanced bi-partition using METIS
- Edge weight:

 $w(a) = -\log(1 - p(a))$



Experimental Results

	# Nodes	# Edges	#Arc Prob: Mean, SD, Quartiles
DBLP	684 911	4 569 982	0.14 ± 0.11, {0.09, 0.09, 0.18}
Flickr	78 322	20 343 018	$0.09 \pm 0.06, \{0.06, 0.07, 0.09\}$
BioMine	1 008 201	13 445 048	0.27 ± 0.21, {0.12, 0.22, 0.36}

Dataset Characteristics



Accuracy Results

	RQ-Tree-MC			RQ-Tree-LB		
	η=0.4	η=0.6	η=0.8	η=0.4	η=0.6	η =0.8
DBLP	0.96	0.99	0.99	1	1	1
Flickr	0.97	0.98	0.98	1	1	1
BioMine	0.95	0.96	0.97	1	1	1

Precision

	RQ-Tree-MC			RQ-Tree-LB		
	η=0.4	η =0.6	η=0.8	η=0.4	η =0.6	η =0.8
DBLP	0.99	0.99	1.00	0.75	0.87	0.91
Flickr	0.98	0.99	0.99	0.76	0.79	0.83
BioMine	0.97	0.98	0.98	0.77	0.81	0.85

Recall



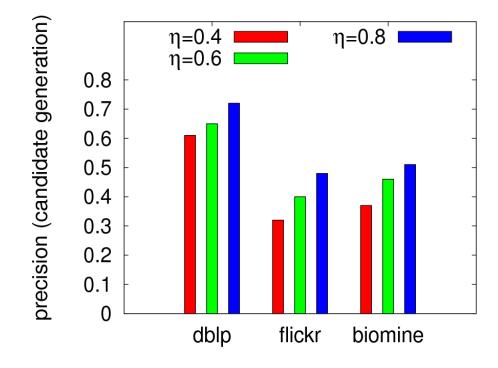
Efficiency Results

	RQ-Tree-MC			RQ-Tree-LB			MC
	η=0.4	η=0.6	η =0.8	η=0.4	η =0.6	η =0.8	All η
DBLP	43	40	36	1.50	0.60	0.60	588
Flickr	60	59	55	0.21	0.20	0.17	114
BioMine	6062	5417	4974	1.00	0.50	0.50	25 608

Online query-processing time (sec)



Pruning Capacity of Filtering Phase

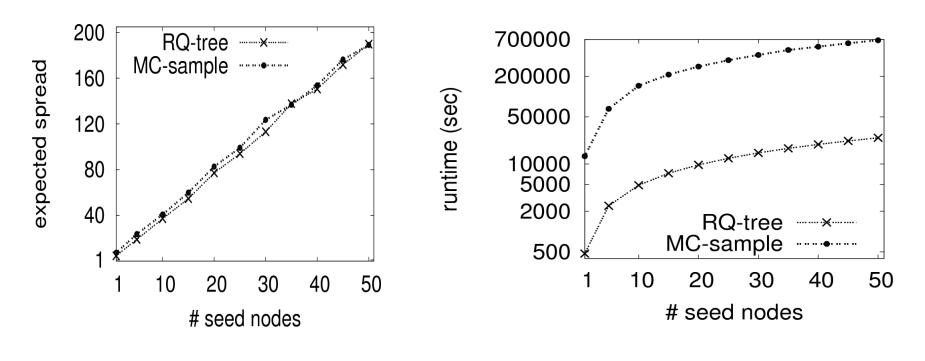


Precision of Filtering Phase

RQ-Tree in Influence Maximization



RQ-Tree index in multi-source reliability query and in influence maximization



Expected Spread (Last.FM)

Top-k Seed Finding Time (Last.FM)



Conclusion

Indexing method for answering online reliability queries efficiently and effectively.

 RQ-tree works very well with lower arc probabilities and with higher probability threshold.

In future, we shall study reliability search queries when the arc probabilities are not independent.



Questions?