



Applications, Algorithms, Experiments, Open Problems

Mattia D'Emidio¹

NetworKit

Large-Scale Network Analysis – Interactive and Fast!

¹Assistant Professor @ UNIVERSITY OF L'AQUILA Lecturer/Scientific Collaborator @ GRAN SASSO SCIENCE INSTITUTE email: mattia.demidio@{univaq,gssi}.it web: www.mattiademidio.com

NetworKit Day 2020

October 15, 2020



Mattia D'Emidio

On Mining Distances out of Massive Time-Evolving Graphs



- Mining Distances: Problem
- 2 Mining Distances vs Modern Applications
- **3** Scalable Mining of Distances
- 4 2-HOP-COVER
- 6 2-нор-cover and Time-Evolving Graphs



Outline



- Mining Distances: Problem
- 2 Mining Distances vs Modern Applications
- 8 Scalable Mining of Distances
- 4 2-HOP-COVER
- 6 2-HOP-COVER and Time-Evolving Graphs



Mining Distances: Problem



MINING DISTANCES FROM (DI)GRAPHS

- Given (DI)GRAPH G = (V, A)
- Given sequence of (DISTANCE) QUERIES $\{q(s_1,t_1),q(s_2,t_2),\ldots\}$ for pairs of vertices $s_i,t_i\in V$
- Report **DISTANCE** $d(s_i, t_i)$ as fast as possible
 - d(s_i, t_i): distance = weight of a shortest path from s_i to t_i in G

RELATED VARIANTS

- **REACHABILITY QUERIES:** report **yes** if there exist a path from s_i and t_i in G, **no** otherwise
- PATH-REPORTING QUERIES: report whole shortest path (sequence of vertices/arcs) if any, empty set otherwise



ONE OF MOST STUDIED PROBLEMS in Computer Science/Engineering

Several highly impacting applications in real-world

- *Routing* in communication networks
- Route/Journey planning road/transport networks
- Context Aware Search, web indexing
- Data mining for linked data, Graph Databases
- Social Networks analysis, Social Engineering
- Bioinformatics, Top-k Nearest Keyword Search

HUGE AMOUNT OF RESEARCH/LITERATURE

Algorithms, data structures, bounds and complexity results

TEXTBOOK/STANDARD SOLUTION

- Solve SSSP (upon query), e.g. Dijkstra's algorithm
- **Cost PER QUERY:** (for an *n*-vertex, *m*-arc graph)
 - $\square \mathcal{O}(m + n \log n)$ time, $\mathcal{O}(n)$ space
- **BEST KNOWN METHOD** for generally positively weighted digraphs



Problem: **SCALABILITY ISSUES** against "modern inputs"



Outline



Mining Distances: Problem

2 Mining Distances vs Modern Applications

8 Scalable Mining of Distances

4 2-HOP-COVER

5 2-HOP-COVER and Time-Evolving Graphs



Mattia D'Emidio

On Mining Distances out of Massive Time-Evolving Graphs

Mining Distances vs Modern Applications

BIG GRAPHS, BIG PROBLEMS

- Polynomial/linear not good enough
- $\mathcal{O}(m + n \log n)$ query algorithm leads to (tens of) seconds per query when graphs are MASSIVE IN SIZE ($\geq 10^5$ vertices/arcs)
- **UNSUSTAINABLE TIME OVERHEAD**, especially for interactive applications executing **thousands/millions queries a day**

GRAPHS EMERGING FROM MODERN APPLICATIONS are indeed MASSIVE

BILLIONS OF VERTICES/ARCS

- e.g. Twitter, Facebook, Google Maps, WWW, Internet
- Moreover they are "COMPLEX"
- No topological features to exploit for accelerating queries
 - e.g. regularity, planarity, power-law degree distributions (committion networks, Internet, Web)



Mining Distances vs Modern Applications

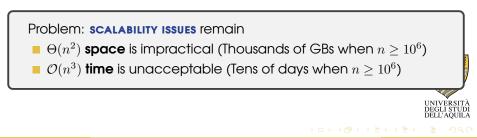


ALTERNATIVE TO STANDARD: USE OF PREPROCESSING

- Quite well established strategy to handle large inputs
 - 1. SOLVE APSP once, e.g. Floyd-Warshall algorithm or repeated Dijkstra's
 - 2. STORE outputs in a DISTANCE MATRIX
 - 3. RETRIEVE distances upon query by accessing right DM location
- Cost per query: $\mathcal{O}(1)$ time/space to access (optimal)

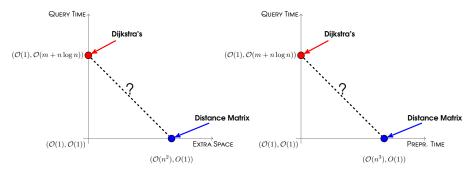
PREPROCESSING COSTS

- $\mathcal{O}(nm + n^2 \log n) \in \mathcal{O}(n^3)$ time
- $\blacksquare n \times n = \Theta(n^2)$ extra space



Query Time vs Extra Space and Prepr. Time







Outline



- Mining Distances: Problem
- 2 Mining Distances vs Modern Applications
- **3** Scalable Mining of Distances
- 4 2-HOP-COVER
- 6 2-HOP-COVER and Time-Evolving Graphs



Scalable Mining of Distances



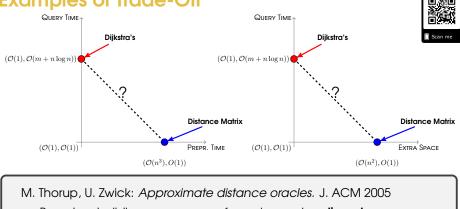
VERY ACTIVE RESEARCH FIELD: various techniques to find trade-offs

- 1. APPROXIMATION
- 2. Sampling
- 3. PARALLELISM
- 4. Restriction to special classes of graphs

SOME LITERATURE (non-exhaustive list):

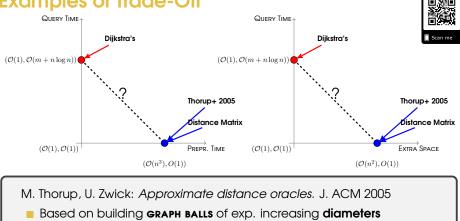
- [Potamias+ CIKM 2009][Elkin+ SODA 2015]
- [Thorup+ JACM 2015][Alstrup+, SODA 2016]
- [Cohen+, SODA 2002, SIAM J. Comp. 2003]
- [Thorup+ JACM 2005][Sarma+ WSDM 2010]
- [Abraham+ ESA 2012][Akiba+ SIGMOD 2013][Delling+ ESA 2014]





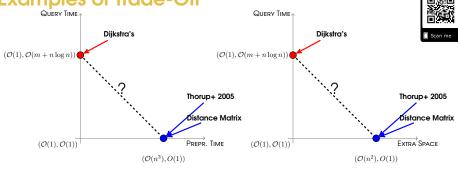
- Based on building GRAPH BALLS of exp. increasing diameters
- PREPROCESSING in $\mathcal{O}(kmn^{\frac{1}{k}})$ expected time
- **EXTRA SPACE** $\mathcal{O}(kn^{1+\frac{1}{k}})$ QUERY in $\mathcal{O}(k)$ time for any $k \ge 1$
- Distances have **STRETCH** $\leq 2k 1$ (i.e. approximated for k > 1)

Equivalent to distance matrix for exact distances k = 1



- **PREPROCESSING** in $\mathcal{O}(kmn^{\frac{1}{k}})$ expected time
- **EXTRA SPACE** $\mathcal{O}(kn^{1+\frac{1}{k}})$ **QUERY** in $\mathcal{O}(k)$ time for any $k \ge 1$
- Distances have **stretch** $\leq 2k 1$ (i.e. approximated for k > 1)

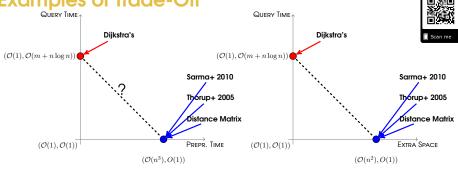
EQUIVALENT TO DISTANCE MATRIX for **exact distances** k = 1



A. D. Sarma, S Gollapudi, M. Najork, R. Panigrahy: A sketch-based distance oracle for web-scale graphs. WSDM 2010: 401-410

- Simplification of method of Thorup and Zwick via **SEED NODES**
- Same theoretical guarantees on **preprocessing** and **space**
- Query in $\widetilde{\mathcal{O}}(n^{\frac{1}{c}})$ time for any $c \geq 1$, stretch 2c-1

Better behavior experimentally, again Equivalent to distance MATRIX for c=1

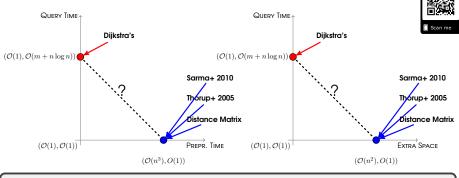


A. D. Sarma, S Gollapudi, M. Najork, R. Panigrahy: A sketch-based distance oracle for web-scale graphs. WSDM 2010: 401-410

- Simplification of method of Thorup and Zwick via **SEED NODES**
- Same theoretical guarantees on **preprocessing** and **space**
- QUERY in $\widetilde{\mathcal{O}}(n^{\frac{1}{c}})$ time for any $c\geq 1$, stretch 2c-1

Better behavior experimentally, again Equivalent to distance MATRIX for c=1

A Notable Trade-Off

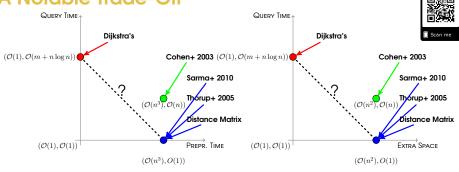


E. Cohen, E. Halperin, H. Kaplan, U. Zwick: *Reachability and Distance Queries via 2-Hop Labels.* SIAM J. Comput. 32(5): 1338-1355 (2003)

- Based on the notion of **2-HOP-COVER** ("compact" representation of transitive closure)
- Several works followed on the same ideas [Abraham+ ESA 2012] [Akiba+ EDBT 2012, SIGMOD 2013] [Delling+ ESA 2014]

DELL'AQUILA

A Notable Trade-Off



E. Cohen, E. Halperin, H. Kaplan, U. Zwick: *Reachability and Distance Queries via 2-Hop Labels.* SIAM J. Comput. 32(5): 1338-1355 (2003)

- Based on the notion of **2-HOP-COVER** ("compact" representation of transitive closure)
- Several works followed on the same ideas [Abraham+ ESA 2012] [Akiba+ EDBT 2012, SIGMOD 2013] [Delling+ ESA 2014]

Worse worst-case but EFFECTIVE IN PRACTICE WITH SUITED HEURISTICS



On the importance of experimentation and tools for (massive) graph processing

- Most RESULTS on shortest-path/distance queries in complex networks are of experimental nature
- For GENERAL GRAPHS no known exact approach PROVABLY BETTER than Dijkstra's and APSP+Distance Matrix in terms of the three criteria (query time, extra space, preprocessing time)
- **EXPERIMENTAL EFFORTS** to determine best solutions
- OF PARAMOUNT IMPORTANCE having EFFECTIVE, EASY TO USE TOOLKITS for
 - manipulation, generation, analysis of large-scale complex networks
 - efficient implementation of graph algorithms
 - many thanks to NETWORKIT COMMUNITY for their effort (more details later)

Outline



- Mining Distances: Problem
- 2 Mining Distances vs Modern Applications
- 8 Scalable Mining of Distances
- 4 2-HOP-COVER
- 6 2-HOP-COVER and Time-Evolving Graphs



2-HOP-COVER

Given directed weighted graphs $G = (V, A, w)^{-1}$

 \blacksquare n = |V| vertices, m = |E| arcs, weight func. $w : A \to \mathbb{R}^+$

- Let P_{uv} be collection of shortest paths for pair $u,v\in V$ in G
- Let $P = \bigcup_{u,v \in V} P_{uv}$ be collection of all shortest paths of G

Hop: a triple (h, u, v) where h is a (simple) **path** and u, v are **endpoints** of such path

A SET OF HOPS H is a 2-hop-cover of G if and only if:

- For any $s, t \in V$ such that $P_{st} \neq \emptyset$ (pair of connected vertices)
- There exists a (SHORTEST) PATH $p \in P_{st}$ and two HOPS $(h_1, s, h), (h_2, h, t) \in H$ such that

$$p = h_1 \oplus_h h_2$$

i.e. p can be reconstructed as **concatenation at hub vertex** h



¹Special cases easy to derive

Mattia D'Emidio





2-HOP-COVER

IN OTHER WORDS



- A 2-нор-соver hop set H allows to **Reconstruct** (the weight of) one shortest path by **concatenating two (shortest) paths** emanating from s and t at a suited нив vertex
- H is said to COVER G (or to satisfy COVER PROPERTY)
- |H| is the **SIZE** of the 2-HOP-COVER

NAIVE BUILDING OF a 2-HOP-COVER

- 1. Start with $H = \emptyset$
- 2. Solve APSP once
- 3. For any found shortest path p from s to t
 - $\blacksquare H = H \cup \{(\emptyset, s, s), (p, s, t)\}$
 - Or $H = H \cup \{(h_1, s, h), (h_2, h, t)\}$ Where h_1 and h_2 are any two disjoint subpaths of p emanating from a common vertex h
- **Result:** *H* has size $\mathcal{O}(n^2)$ (# triples)

Moreover **RETRIEVAL** of shortest paths from H requires **SEARCHING** ($\mathcal{G}_{\mathcal{H}}$



2-HOP-COVER

MORE EFFICIENT RETRIEVAL



- **CONVERT** into 2-HOP-COVER **distance labeling** data structure
- Well known from distributed computing
- STORES data at each vertex in label form
- ALLOWS retrieval of distances/paths by accessing only labels of involved vertices

Populating 2-HOP-COVER DISTANCE LABELING from 2-HOP-COVER hop set H:

For any
$$(h_1, s, h), (h_2, h, t) \in H$$

ADD entry $(h, w(h_1))$ to $L_o(s)$ (outgoing label of s) with $w(h_1) = d(s, h)$

ADD entry $(h, w(h_2))$ to $L_i(t)$ (incoming label of t) with $w(h_2) = d(h, t)$

DISTANCE (2-HOP-COVER) LABELING is

$$L = \{\{L_o(v)\}_{v \in V}, \{L_i(v)\}_{v \in V}\}$$



QUERY ALGORITHM for 2-HOP-COVER distance labeling

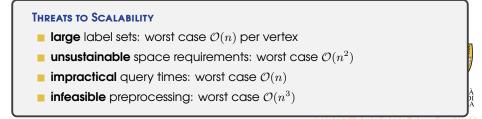
$$\mathsf{Q}(s,t,L) = \begin{cases} \min_{v \in V} \{\delta_{sv} + \delta_{vt} \mid (v, \delta_{sv}) \in L_o(s) \land (v, \delta_{vt}) \in L_i(t) \} & \text{if } L_o(s) \cap L_i(t) \neq \emptyset \\ \infty & \text{otherwise} \end{cases}$$

L_o(s) \cap L_i(t) $\neq \emptyset$ denotes the two label sets share a **common hub vertex** If **labels sorted by vertex**, query algo takes

 $\mathcal{O}(\max_{s,t\in V, s\neq t} \{\max\{|L_i(s)|, |L_o(t)|\}\})$

 $\Theta(n)$ with **NAIVE 2-HOP-COVER** computation, on top of $\mathcal{O}(n^2)$ extra space

More compact hop sets/LABELS necessary for practical usage



Scalable 2-HOP-COVER Distance Labelings



(NEGATIVE) FACTS

- NP-Hard to compute minimum-sized 2-нор-соvеr hop set (from min set cover)
- NP-HARD to find a corresponding minimum-sized distance labeling
- $\ \ \, \Omega(n^{4/3})$ Lower bound on the size of any labeling scheme (sum of sizes of all label sets)
- A $\mathcal{O}(\log n)$ -factor APPROXIMATION ALGORITHM running in $\mathcal{O}(mn^2 \log(\frac{n^2}{m}))$ time is known (again useless at large scale)



Scalable 2-HOP-COVER Distance Labelings

(POSITIVE) FACTS



- Akiba et al. Fast exact shortest-path distance queries on large networks by pruned landmark labeling. SIGMOD 2013: 349-360
- Simple POLY-TIME HEURISTIC FOR PREPROCESSING (PLL) that computes MIN-IMAL LABELINGS (ML)
 - Any labeling such that any removal of any label entry breaks COVER PROP-ERTY
 - Certain types of ML (well-ordered ones) perform very well in practice
- Variant of PLL, named RXL, given in [Delling+ ESA 2014]

INGREDIENTS OF PLL/RXL

VERTEX ORDERING (according to some "importance criterion")

SHORTEST PATH (Dijkstra's like) visits

PRUNING mechanism

]. Fix a vertex ordering $\{v_1, v_2, \ldots, v_n\}$



- 2. **PERFORM** 2n (*n* forward, *n* backward) Dijkstra's-like visits, each rooted at a vertex $v_i \in V$
- 3. INCREMENTALLY ENRICH LABELING L as follows:
 - L^{k-1} status of labeling after execution of SP visits rooted at v_{k-1}

Initially
$$L_i(v)^0 = L_o(v)^0 = \emptyset$$

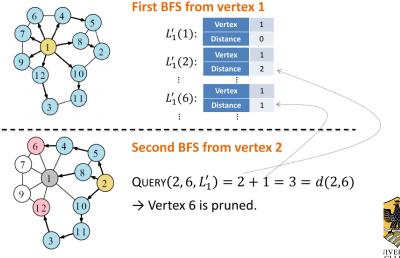
- 3.1 During visit rooted at v_k on G (or G^T) if vertex u settled with distance δ
- 3.2 CHECK whether $Q(v_k, u, L^{k-1}) \leq \delta$ (or $Q(u, v_k, L^{k-1}) \leq \delta$)
- 3.3 IF YES \implies visit is **PRUNED** at u
- 3.4 IF NO \implies ADD (v_k, δ) to $L_i(u)$ (or $L_o(u)$) and CONTINUE

PRUNING STEP: means L^{k-1} already covers pair (v_k, u) (or (u, v_k)) **Holds** for all pairs (v_k, x) (or (x, v_k)) such that a shortest path from v_k to x (for rom x to v_k) passes through u

Pruned Landmark Labeling

Preprocessing

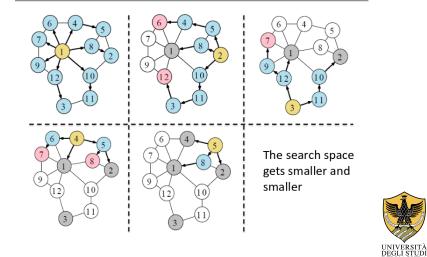




Pruned Landmark Labeling

Preprocessing





25 / 48

DELL'AOUILA



1	-
	5
	6

VERTEX	$L_o(\cdot)$	$ L_i(\cdot) $
0	$\{(4,1),(0,0)\}$	$\{(4,1),(0,0)\}$
1	$\{(4,2),(0,1),(3,2),(1,0)\}$	$\{(4,2),(0,1),(3,2),(1,0)\}$
2	$\{(4,2),(0,2),(3,1),(1,1),(2,0)\}$	$\{(4,2),(0,2),(3,1),(1,1),(2,0)\}$
3	$\{(4,1),(3,0)\}$	$\{(4,1),(3,0)\}$
4	$\{(4,0)\}$	$\{(4,0)\}$
5	$\{(4,1),(5,0)\}$	$\{(4,1),(5,0)\}$
6	$\{(4,2),(5,1),(6,0)\}$	$\{(4,2),(5,1),(6,0)\}$

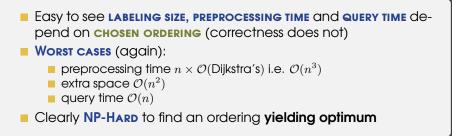
Sample graph and a corresponding 2-HOP-COVER distance labeling w/ vertex ordering $\{4,0,3,1,2,5,6\}$

WELL ORDERED property (nice property to exploit)

DELL'AQUILA

Performance





VERY GOOD EXPERIMENTAL BEHAVIOR when ordering found via fast-to-compute centrality measures

degree, approx betweenness, number of covered pairs (greedy)

GOOD BEHAVIOR means, even on billion-vertex networks:

- **Preprocessing** \approx hours
- **Space occupancy** \approx tens of GBs
- **QUERY TIME** \approx milliseconds



	label s	pre	preprocessing [s]		5	space [MiB]			query [µs]					
instance	PLL	RXL	PLL	Tree	RXL	CRXL	PLL	Tree	RXL	CRXL	\overline{PLL}	Tree	RXL	CRXL
Gnutella*	644×16	791	54	209	307	451	209	68	95.7	49.1	5.2	19.0	7.1	45.9
Epinions*	33×16	118	2	128	31	39	32	42	19.1	7.7	0.5	11.0	1.1	4.1
$Slashdot^*$	68×16	219	6	343	85	110	48	83	37.4	17.8	0.8	12.0	1.7	8.0
NotreDame*	34×16	25	5	243	18	22	138	120	22.9	11.9	0.5	39.0	0.2	1.0
$WikiTalk^*$	34×16	113	61	2459	1076	1278	1000	416	560.8	86.5	0.6	1.8	1.0	3.4
Skitter	123×64	273	359	_	2862	3511	2700	_	1074.6	316.7	2.3	_	2.3	20.6
Indo*	133×64	43	173	_	173	201	2300	-	158.6	90.2	1.6	-	0.5	1.8
MetroSec	19×64	116	108	_	2300	2573	2500	_	592.8	207.7	0.7	_	0.8	3.6
Flickr*	247×64	360	866	_	5888	7110	4000	_	1794.6	345.9	2.6	_	2.8	19.9
Hollywood	$2098\!\times\!64$	2114	15164	_	61736	75539	12000	_	5934.3	2050.0	15.6	_	13.9	204.0
Indochina*	415×64	91	6068	_	8390	8973	22000	_	1978.8	876.8	4.1	_	0.9	3.9

TODO:

- Evaluate RXL on weighted (sparse) digraphs
- Evaluate CRXL: compressed version compromising on query time to save space
- Evaluate APPROXIMATION ALGO

UNIVERSITÀ DEGLI STUDI

Limits of Preprocessing in Modern Networks



"Problem": REAL-WORLD NETWORKS ARE TIME-EVOLVING (aka dynamic)
 Topology and arc weights likely to change over time

EXAMPLES:

- Social Networks: new friends, removed friends/pages
- **WEB GRAPHS:** new pages/links, broken links, removed pages
- **BLOGGING:** new replies/posts, removed users/posts/replies
- COLLABORATION NETWORKS: new/withdrawn papers
- INFRASTRUCTURES: disruptions, new roads, cancelled flights
- GRAPH DATABASES: updated/outdated entries



Limits of Preprocessing

ALL PREPROCESSING-BASED TECHNIQUES suffer of the following issues:



- PRECOMPUTED DATA can become outDated/INCORRECT due to updates to the graph
- **PRECOMPUTED DATA** require time-consuming preprocessing
- RE-PROCESSING after any update: impractical in terms of time overhead
- **ENRICHING** data structure to tolerate updates to graph: infeasible due to huge space overheads

FOR 2-HOP-COVER LABELINGS:

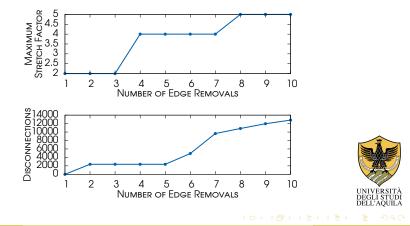
- Label entries can become **outdated** (i.e. hop contain obsolete distances)
- Large number even in presence of A SINGLE ARC UPDATE
- Even a single update can lead to LARGE NUMBER OF INCORRECT AND TO QUERIES
 - \blacksquare $q_1(s_1, t_1), q_2(s_2, t_2), \ldots$ queries depends on status of graph G_i



Limits of Preprocessing

EFFECTIVE DYNAMIC ALGORITHMS are necessary

- Algorithms able to update only the part of the data structure that is compromised by the change
- **EFFECTIVE** typically means faster (enough) wrt scratch recomputation





Limits of Preprocessing



DYNAMIC ALGORITHM: updates existing labeling when **GRAPH UNDER-GOES CHANGES**

- Exploit current data structure to identify compromised entries
- In this specific case: we want **COVER PROPERTY** to remain true after each update



Outline



- Mining Distances: Problem
- 2 Mining Distances vs Modern Applications
- 8 Scalable Mining of Distances
- 4 2-HOP-COVER
- **б** 2-нор-соver and Time-Evolving Graphs



2-нор-cover and Time-Evolving Graphs



DYNAMIC PROBLEM, two flavors:

- **INCREMENTAL:** vertex/arc insertions, arc weight decreases
 - Usually EASIER TO HANDLE
- **DECREMENTAL:** vertex/arc deletions, arc weight increases
 - Typically more computationally challenging

DYNAMIC ALGORITHMS FOR 2-HOP-COVER LABELINGS

- INCREMENTAL ALGORITHM [Akiba+, WWW 2014]
- **DECREMENTAL ALGORITHM(S)** [D'Angelo, D'Emidio, Frigioni, ACM JEA 2019] [D'Emidio, MDPI Algorithms 2020]



Incremental Algorithm (RESUME-2HC) [Akiba+ WWW 2014]



Input: Arc (x, y) undergoes incremental update foreach $v_i \in L(u) \cup L(v)$ do

- **2 RESUME** BFS/Dijkstra's rooted at v_i from vertices x and y;
 - ADD new pairs if pruning test passed;

MAIN FEATURES:

3

- LAZY ALGORITHM: outdated entries NOT REMOVED
- RESUME-2HC only ADDS SHORTER DISTANCES induced by incremental updates
 - **REMOVING** non-shortest-path distances is computationally expensive
- **CORRECTNESS** holds since query algo searches for minimum
- **LABELING SIZE** inevitably grows with number of updates
- \Longrightarrow Minimality not preserved



Incremental Algorithm (RESUME-2HC) [Akiba+ WWW 2014]



Worst case running time: $\mathcal{O}(n \times \text{Dijkstra's})$

- IN PRACTICE
- VERY EFFECTIVE, on all tested inputs
- MILLISECONDS for updating extremely large labelings
- Whereas PLL takes HOURS OF REPREPROCESSING

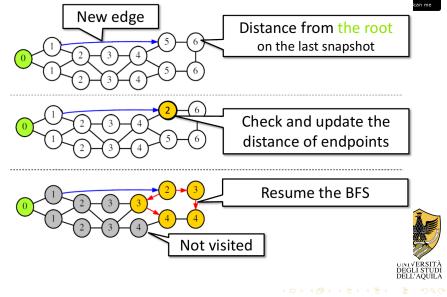
OPEN PROBLEM: design algorithm that **does not break minimality**

PERIODICAL REPROCESSING necessary if labeling size "grows too much" (performance degrades over time)



Example of RESUME-2HC execution





Decremental Algorithm(s)

[D'Angelo, D'Emidio, Frigioni, ACM JEA 2019][D'Emidio, MDPI Algorithm 2020]



DECREMENTAL OPERATIONS MORE difficult to handle: OUTDATED ENTRIES MUST BE REMOVED

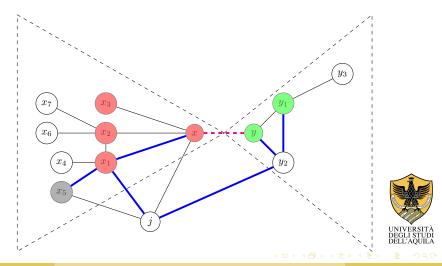
otherwise correctness not guaranteed

DECREMENTAL ALGO #1 (BIDIR-2HC) – [D'Angelo, D'Emidio, Frigioni, ACM JEA 2019]

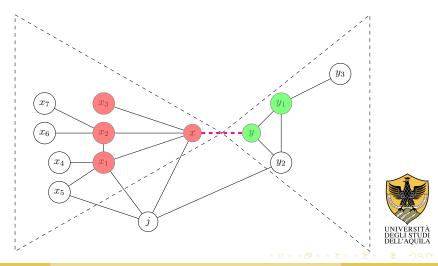
THREE PHASES

- 1. **IDENTIFICATION OF AFFECTED VERTICES** (potentially containing outdated entries)
 - use induced paths
- 2. REMOVAL of outdated (w/ binary search)
- RESTORE OF COVER PROPERTY by suited SP visits (in order) rooted at affected vertex

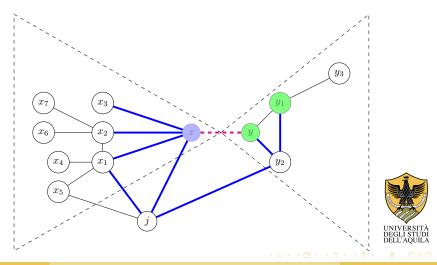
IDENTIFICATION: red/green vs gray vertices connected by s-paths containing/not containing modified arc (can be checked via content of label sets)



REMOVAL of green entries from red outgoing labels and red entries from green incoming labels (linear scan)



Restore one **forward** visit (of G) per **red** vertex one **backward** visit (of G^T) per **green** vertex (to **re-cover** pairs)





Worst case running time: $\mathcal{O}(nm\log n + n^3)$

- Looks bad but in practice RATHER EFFECTIVE IN ALL INSTANCES
- At most, on average, TENS OF SECONDS for updating extremely large labelings
- Where PLL takes HOURS FOR REPREPROCESSING

PROBLEM: SIOW ON SOME SPARSE, WEIGHTED DIGRAPHS

Not so rare cases slower than from scratch (even if better on average)



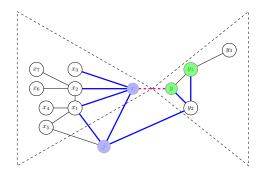
Mattia D'Emidio

REASON: less effective pruning mechanism

- Leads to unnecessary exploration of parts of the graph
- Large fractions execution time spent on this step (PROFILING)

LESS EFFECTIVE PRUNING

- Visits traverse non-affected vertices
- Pruning can stop visit only for pairs of affected vertices
- **VISIT** from x to y **CANNOT STOP** j (although x and j are covered)





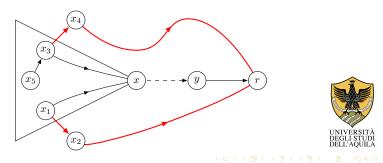


DECREMENTAL ALGO #2 (QUEUE-2HC) - [D'Emidio, Algorithms 2019]

MAIN DIFFERENCES:

Scan me

- **IDENTIFICATION** and **REMOVAL** combined in single step (use induced trees)
- **RESTORING DOES NOT TRAVERSE** unchanged vertices
- Exploits label entries of unchanged vertices to AVOID UNNECESSARY EX-PLORATIONS (such entries encode shortest paths in new graph)
- Can be used to **re-cover pairs**
- **EVALUATES** them via **PRIORITY QUEUE**, in order



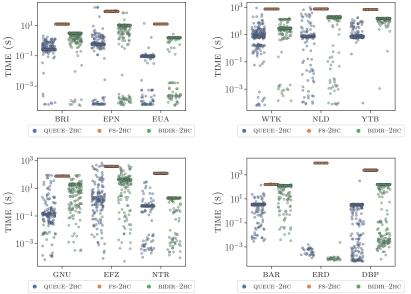
Some Experimentation



Dataset	Network Type	V	E	avg deg	S	D	W
CAIDA (CAI)	Ethernet	3.20e+04	4.01e+04	2.51	0	0	٠
LUXEMBOURG (LUX)	Road	3.06e+04	7.55e+04	4.11	0	٠	•
WGTGNUTELLA (GNU)	Peer2Peer	6.26e+04	1.48e+05	4.73	0	٠	•
Brightkite (bkt)	Location-based	5.82e+04	2.14e+05	7.35	0	0	0
EFZ (EFZ)	Railway	1.25e+05	4.02e+05	6.43	0	٠	٠
EU-ALL (EUA)	EMAIL	2.65e+05	4.19e+05	2.77	0	٠	0
Epinions (epn)	Social	1.32e+05	8.41e+05	12.76	0	٠	0
Barabási-A. (baa)	Synthetic (Power-Law)	6.32e+05	1.00e+06	3.17	٠	0	٠
web-NotreDame (NTR)	HyperLinks	3.26e+05	1.09e+06	6.69	0	0	0
NETHERLANDS (NLD)	Road	8.92e+05	2.28e+06	5.11	0	٠	•
YouTube (утв)	Social	1.13e+06	2.99e+06	5.26	0	0	0
WikiTalk (wtk)	COMMUNICATION	2.39e+06	5.02e+06	4.19	0	٠	0
Human-Genome (bio)	Biological	1.43e+04	9.03e+06	1262.94	0	0	•
AS-Skitter (ski)	Computer	1.70e+06	1.11e+07	13.08	0	0	0
DBPedia (dbp)	Knowledge	3.97e+06	1.29e+07	6.97	0	٠	9
Erdős-Rényi (erd)	Synthetic (Uniform)	1.00e+04	2.50e+07	2499.11	•	9	



Some Experimentation



On Mining Distances out of Massive Time-Evolving Graphs

44 / 48

ERSITÀ I STUDI AQUILA

OPEN (ON-GOING) WORK



- MINIMALITY PRESERVING incremental algorithm
- **IMPROVE** further decremental algorithm, or find some lower bound
- REFINE theoretical analysis (output bounded sense?)
 - Theoretical foundations to explain inaccuracy of worst case
- BATCH algorithms
- ATTACK other big time-evolving graph mining problems via similar techniques (or adapt dynamic algo to relevant special cases e.g. TIMETABLE QUERIES)
- DISTRIBUTED preprocessing/dynamic algorithms
- STRENGTHEN experimental results
 - More inputs
 - Better evaluation of RXL/CRXL (adaptation of dyn algo?)
 - Evaluation of apx algo



NetworKit: key features in this context GRAPHS

- **Easy, effective** graph manipulation/processing tools
- All basic graph algorithms, also EASILY CUSTOMIZABLE
- Support for graph update operations

NETWORK ANALYSIS

- PERFORMANCE-CRITICAL ALGORITHMS implemented in C++/OpenMP
- **CENTRALITY MEASURES** (degree distrib. in $\mathcal{O}(n)$, easily parallelizable)
- IMPLEMENTATION OF VERY RECENTLY INTRODUCED ALGORITHMS: parallel implementations of two approx algorithms for Betweenness centrality

GRAPH GENERATORS/INPUT INTERFACES

- Erdös-Renyi Model, Barabasi-Albert models for random graphs
- Readers for datasets from known repositories (SNAP, Konect)

INTEGRATION WITH PYTHON FOR DATA ANALYSIS AND INTEROPERABILITY

pandas, numpy, scipy, networkx

For EDUCATIONAL PURPOSES (courses: big data processing, algorithmengineering)

interactive workflow and seamless Python integration







(Some) Publications supported by NetworKit



M. D'Emidio, I. Khan, D. Frigioni: Journey Planning Algorithms for Massive Delay-Prone Transit Networks. Algorithms 13(1): 2 (2020)

M. D'Emidio: Faster Algorithms for Mining Shortest-Path Distances from Massive Time-Evolving Graphs. Algorithms 13(8): 191 (2020)

G. D'Angelo, M. D'Emidio, D. Frigioni: Fully Dynamic 2-Hop Cover Labeling. ACM J. Exp. Algorithmics 24(1): 1.6:1-1.6:36 (2019)

M. D'Emidio, I. Khan: Dynamic Public Transit Labeling. ICCSA (1) 2019: 103-117





Thanks for your attention

Q&A

mattia.demidio@{univaq,gssi}.it www.mattiademidio.com



Mattia D'Emidio

On Mining Distances out of Massive Time-Evolving Graphs