

Metric Repair - Hardness and Approximation(s)

Qualifying Exam Presentation

Based on *Metric Violation Distance: Hardness and Approximation* [FRB22]
and *Fitting Metrics and Ultrametrics With Minimum Disagreements*
[CAFLDM22]

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July 2, 2024

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1. The Problem of Metric Repair
2. Hardness of Metric Repair
 - Decrease Only is Easy
 - Everything Else is Hard
3. Approximation Algorithms
 - First Approximation Algorithm
 - Second Approximation Algorithm
4. Future (read - current) Work

The Problem of Metric Repair

- **Data Processing:** Many Data processing tasks (e.g, clustering) rely on the structural properties of data, such as satisfying the triangle inequality.

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- **Graph Problems:** Hard graph problems become significantly easier when weights satisfy the triangle inequality (e.g, TSP).
- Perhaps a good idea would be to find a metric that is "near" the given distance measures.

Problem Definition

(K_n, w) is a complete, positively weighted graph.

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Definition (Broken Triangle)

We say that a triangle $\{i, j, k\} \subset V$ is **broken** if $M_{i,j} > M_{i,k} + M_{j,k}$. In this case, we say that $\{i, j\}$ is **heavy** in $\{i, j, k\}$, and the other two edges are **light**. The **deficit** of $\{i, j, k\}$ is $\delta(\{i, j, k\}) := M_{i,j} - (M_{i,k} + M_{j,k})$.

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We say M is **metric** if no triangle in M is broken.

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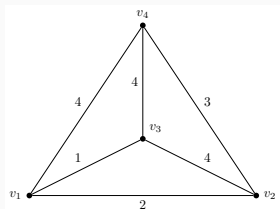
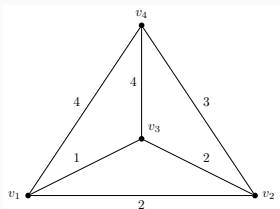
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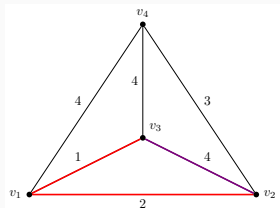
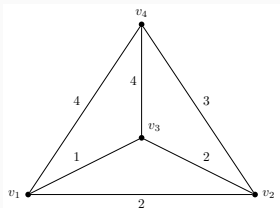
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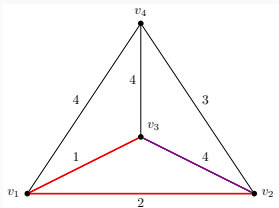
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Given (K_n, w) the problem of **Metric Repair** asks to find $w' : \binom{[n]}{2} \rightarrow \mathbb{R}_{>0}$ such that (K_n, w') is metric. A solution is **optimal** if $\|w' - w\|_0$ is minimal.

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- $w' \geq w$: Increase Only Metric Repair (**IOMR**).
- $w' \leq w$: Decrease Only Metric Repair (**DOMR**).
- Otherwise: **General Metric Repair (MR)**.



Hardness of Metric Repair

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 - If $w(u, v) > \text{dist}_w(u, v)$, set $w'(uv) = \text{dist}_w(u, v)$
- What about MR or IOMR?

Theorem ([FRB22])

The decision version of MR (and IOMR) is NP complete.

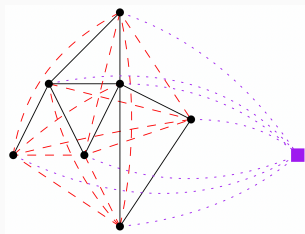
- ***k-Vertex Cover***: Given $G = (V, E)$, is there a subset $V' \subset V$ of size $|V'| \leq k$ such that every edge in G is incident with a vertex in V' ?
- ***k-Metric Repair***: Is there a collection of at most k edges that changing them results in a metric graph?

We reduce $k - \text{VTX} \leq_p k - \text{MR}$.

Proof.

Given a graph $G = (V, E)$, we construct a complete graph $(V \cup \{v_0\}, \binom{V \cup \{v_0\}}{2})$ with weights:

$$w(u, v) = \begin{cases} 2 + \varepsilon & uv \in E \\ 2 & uv \notin E \text{ and } u, v \neq v_0 \\ 1 & u = v_0 \text{ or } v = v_0 \end{cases}$$



The reduction, from [FRB22]

All broken triangles in the constructed graph must be of the form $\{v_0, u, v\}$, and every edge $uv \in E$ defines such triangle. \square

Approximation Algorithms

Theorem ([FRB22])

There exists an $O\left(OPT^{1/3}\right)$ approximation algorithm for MR and IOMR that runs in $O(n^6)$ time.

Theorem ([CAFLDM22])

*There exists a randomized algorithm that gives an **expected** $O(\log(n))$ approximation and runs in $O(n^3)$ time. This algorithm only holds for MR.*

Definition

A collection of edges S is a **cover** for \mathcal{C} if it's a hitting set for \mathcal{C} . A cover is **light** if it contains a light edges from each broken cycle.

Theorem ([FGR⁺19])

Let \mathcal{C} be the collection of all broken cycles in (K_n, w) . Then $S \subset E$ is a valid solution to MR (IOMR) if and only if S is a (light) cover for \mathcal{C} .

Proof.

For hard direction:

- For $xy \in S$, set $w'(xy) = \min \{ \text{dist}_{K_n \setminus S, w}(x, y), \|w\|_\infty \}$
- When we remove S , no broken cycles remain - so edges are shortest paths between endpoints
- so no edge that was modified to $\text{dist}_{K_n \setminus S}$ is heavy.
- For edges that were set $\|w\|_\infty$ - we must have disconnected the graph when removing S . We removed at least 2 edges, and a cycle with multiple maximal weights is not broken.

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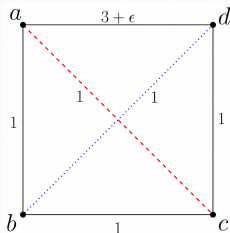
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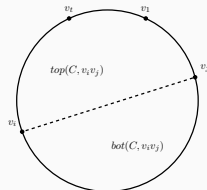


Small cycles are not enough. [CAFLDM22]

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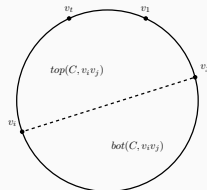
A **unit cycle** is a broken cycle C where for each chord e , either $bot(C, e)$ is not broken, or $bot(C, e)$ is broken with e not being the heavy edge.

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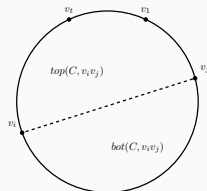
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Claim

Let S be a light cover of all unit cycles in (K_n, w) . Then S is a light cover of C .

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Proof.

If C is non-unit, then there is a chord e such that $bot(C, e)$ is broken and e is heavy. "Propagate downwards" - smallest one must be unit □

First Approximation Algorithm: Strategy

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4. return $S_c \cup S_k$.

First Approximation Algorithm: Cover small cycles

Claim

Let $C_{\leq k}$ be the collection of all broken cycles of size at most k in (K_n, w) . Then one can compute a light cover S_k for $C_{\leq k}$ in $O(n^k)$ time, and $|S_k| \leq (k-1)|opt_k|$.

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$|S_k| \leq (k-1)|opt_k|$ since whenever we encounter an uncovered set, any solution would add at least one edge to opt_6 , while we add at most $(k-1)$.

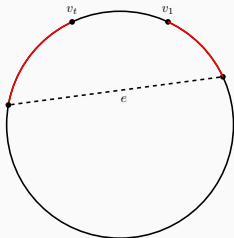
□

First Approximation Algorithm: Chords of large unit cycles

Corollary

Let S_k be as before, and C be a unit cycle uncovered by S_k . Let e be a chord of C such that $|top(C, e)| \leq k$. Then $e \in S_k$.

Proof.



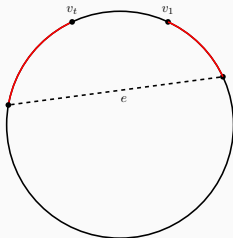
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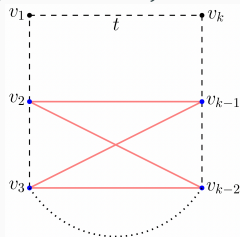
- We need to cover uncovered unit cycles of size at least k .
- Each such cycle has many chords in S_k .
- These chords induce cycles that help us!

□

First Approximation Algorithm: Formalizing cover for large Unit cycles

From now on $k = 6$

For a broken cycle C with $|C| > 6$ and heavy edge v_1v_k , and consider the edge-induced 4-cycle closest to (but not touching) v_1v_k

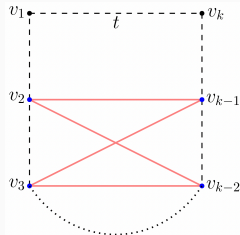


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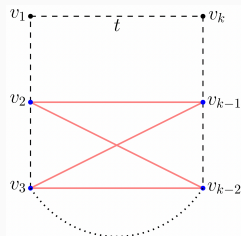
$embed4(C)$ [FRB22]

Observation: chords of this cycle are light edges of C . Moreover, these cycles appear in S_6 for each uncovered unit cycle C .

Lemma

Let S_6 be as before, and let S_c be a set of edges containing a chord of every 4-cycle induced by S_6 . Then $S_6 \cup S_c$ is a solution to IOMR.

First Approximation Algorithm: Chording 4-cycles

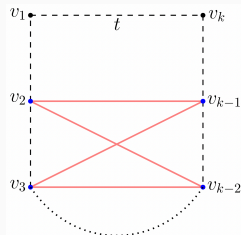


*embed*₄(C) [FRB22]

We find a chord- cover for all 4-cycles in S_6 :

1. $S_c \leftarrow \emptyset$
2. For each 4-cycle $v_2 v_{k-1} v_3 v_{k-2}$ in S_6 , if $v_2 v_3 \notin S_c$ and $v_{k-1} v_{k-2} \notin S_c^a$,
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We know $|S_6| \leq 5|opt_5| \leq 5|OPT|$. If we can bound $|S_c|$ as a function of $|S_6|$, we will get an approximation.

^a $v_{k-1}v_{k-2}, v_2v_3$ need not be in S_6

First Approximation Algorithm: Chording 4-cycles: Not too many edges

Let $G = (V, S_6)$ be the graph induced by the edges in S_6 , and let $\tilde{\mathcal{C}}$ be the collection of cycle from which we added edges to S_c .

- No two cycles in $\tilde{\mathcal{C}}$ can share a chord, so $|S_c|/2 = |\tilde{\mathcal{C}}|$

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Lemma

Let $G = (V, E)$ be a graph whose edge set comprised of a collection of 4-cycles $\tilde{\mathcal{C}}$, no two of which share a chord. Then $|\tilde{\mathcal{C}}| = O(|E|^{\frac{4}{3}})$.

Proof

First Approximation Algorithm: The Algorithm

Algorithm 1 Approximate IOMR

Input: K_n, w

- 1: Compute S_6 using standard HS approximation.
 - 2: Compute S_c using S_6 as described before.
 - 3: **return** $S_6 \cup S_c$.
-

Theorem

Algorithm 1 is an $O(OPT^{\frac{1}{3}})$ approximation to IOMR.

Proof.

OPT is the size of a minimum HS for C . Clearly $|opt_5| \leq OPT$, and so $|S_6| = O(OPT)$. By the previous lemma, $|S_c| = O(|S_6|^{\frac{4}{3}}) = O(OPT^{\frac{4}{3}})$. □

- *Ransomized* algorithm.
- $\log(n)$ approximation *in expectation* (exponentially better!)
- $O(n^3)$ runtime.
- Cannot be (naively) modified to solve IOMR.

Second Approximation Algorithm: Intuition

- If (K_n, w) is metric, then there are no broken triangle.
- Conversely - if there is a broken triangle, (K_n, w) is not metric.

Algorithm 2 Pivot

Input: K_n, w, i

```
1: for  $j, k \in \binom{[n] \setminus i}{2}$  do
2:   if  $w(jk) > w(ij) + w(ik)$  then
3:      $w(jk) = w(ij) + w(ik)$ 
4:   if  $w(jk) < |w(ij) - w(ik)|$  then
5:      $w(jk) = |w(ij) - w(ik)|$ 
```

Claim

After pivoting at i , no broken triangles incident to i remain.

Second Approximation Algorithm: The algorithm

Algorithm 3 Randomized IOMR

Input: K_n, w

- 1: Pick $i \in [n]$ uniformly at random
 - 2: Pivot at i
 - 3: Call Randomized IOMR on $K_n \setminus \{i\}, w|_{[n] \setminus \{i\}}$
-

After pivoting at i , we don't change any edge incident to i anymore.

Lemma

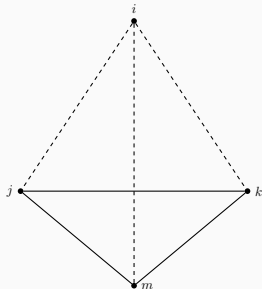
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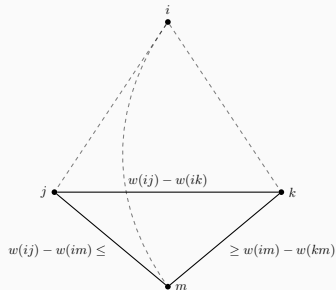
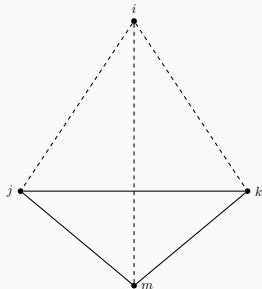


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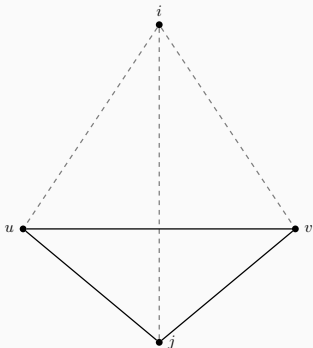
$$w(ij) - w(im) \leq w(ij) - w(ik) \geq w(im) - w(km)$$

□

Second Approximation Algorithm: Approximation intuition

Lemma

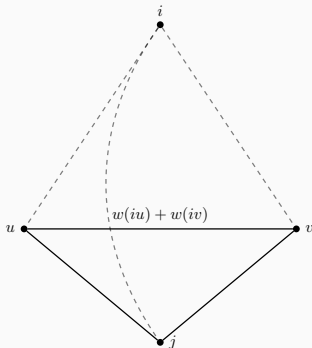
Let uv be an edge that is adjacent to k broken triangles, in which uv is heavy. Order the third vertex of said triangles in order $1, \dots, k$ such that $\delta(uvi) \geq \delta(uvj)$ for $j \geq i$. Then pivoting at i fixes $\{u, v, j\}$ for all $j \geq i$.



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w' are the weights after pivoting at i .

1. $w'(uv) \leq w'(ju) + w'(jv)$:
 - $\delta_i \leq \delta_j$, so $w(iu) + w(iv) \leq w(ju) + w(jv)$.
 - WLOG $w'(uj) = w(ui) + w(ij)$
 - But $w'(vj) \geq w(vi) - w(ij)$
2. $w'(uv) \geq |w'(ju) - w'(jv)|$.
 - $w(iu) + w(iv) < w'(ju) - w'(jv)$.
 - Since $w'(uj) \leq w(ij) + w(iu)$ and $w(ij) \leq w(iv) + w'(jv)$, we obtain contradiction.

Second Approximation Algorithm: Summary

- The algorithm makes progress
- The algorithm fixes "about half" of the broken triangles incident to any edge at each step

How do we formalize this? Let \mathcal{T} be the collection of triangles, and \mathcal{T}' the broken triangles.

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Where the Fractional Packing problem is

$$\max_{p \in [0,1]^{|\mathcal{T}'|}} \sum_{t \in \mathcal{T}'} p_t \quad \text{s.t.} \quad \forall e \in \binom{[n]}{2}, \sum_{t \ni e} p_t \leq 1$$

If we find some α and p_t such that $\sum_{t \ni e} \frac{p_t}{\alpha} \leq 1$, we have an α approximation

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- $\mathbb{E}[|ALG|] \leq \sum_{t \in \mathcal{T}} p_t = \sum_{t \in \mathcal{T}'} p_t$.

Second Approximation Algorithm: Proof Ideas

Fix e .

- When A_t happens, it changes e with probability $1/3$, so $\alpha(e) := \mathbb{E}[\text{\#times } e \text{ was modified}] = \sum_{t \ni e} p_t / 3$.
- We induct on n' , the number of broken triangles e is incident to.
- Let $c_e(n')$ be an upper bound on the expected number of modifications of e when it is incident to n' broken triangles.
- Any partitioning $n_1 + n_2 = n'$ corresponds to possible increase/decrease of e when pivoting.
- We use conditional probability on all such partitions, and later condition on "how big" the deficit was when we pivot.
- "Isoperimetric" qualities simplify our computation, as well as Stirling's approximation.

Details

- An *Ultrametric* is a metric d with the property that

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- Because of this additional structure - possible to get a better approximation ratio. Namely, $O(1)$ approximation!
- The idea is to use ***correlation clustering*** in a sophisticated way (because of ball structure of the metric).

Future (read - current) Work

- *Generalized* metric repair - $(G = (V, E), w)$ where triangle inequalities are *cycle* inequalities.

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Thank You! Questions?

Second Approximation Algorithm: Proof

For n_1, n_2 such that $n_1 + n_2 = n'$, let E_{n_1, n_2} be the event that pivoting at n_1 of the triangles induces an increase, and n_2 induces a decrease. Conditioned on E_{n_1, n_2} , for $k \in [n_1]$ let F_{k, n_2} be the event that the pivot chosen induced the k th largest increase (similarly define $G_{n_1, k}$). [Back](#)

Second Approximation Algorithm: Proof

$$\begin{aligned} c_e(n') &\leq \\ &\leq 1 + \sum_{i \in [n']} c_e(i) \Pr[i \text{ broken triangles remain after pivoting}] \leq \end{aligned}$$

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&\leq 1 + \sum_{n_1, n_2} \Pr[E_{n_1, n_2}] \left(\sum_{k=1}^{n_1} \Pr[F_{k, n_2}] c_e(n_2 + k - 1) + \sum_{k'=1}^{n_2} \Pr[G_{n_2, k'}] c_e(n_1 + k' - 1) \right) \\
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&\leq 1 + \max_{n_1 + n_2 = n'} \left(\sum_{k=n_1+1}^{n'} \frac{1}{n'} c_e(k - 1) + \sum_{k'=n_2+1}^{n'} \frac{1}{n'} c_e(k' - 1) \right) \\
&\leq 1 + \sum_{k=\lfloor n' \rfloor + 1}^{n'} \frac{1}{n'} c_e(k - 1) + \sum_{k=\lceil n' \rceil + 1}^{n'} \frac{1}{n'} c_e(k - 1) \\
&\leq 1 + \frac{1}{n'} c \ln \left(\frac{(n'!)^2}{\lfloor n' \rfloor! \lceil n' \rceil!} \right) \leq c \ln(n' + 1)
\end{aligned}$$

Proof of Combinatorial Lemma






Lemma

Let $G = (V, E)$ be a graph whose edge set comprised of a collection of 4-cycles $\tilde{\mathcal{C}}$, no two of which share a chord. Then $|\tilde{\mathcal{C}}| = O(|E|^{\frac{4}{3}})$.

Proof.

- Let V_s be the vertices in G of degree $\leq |E|^{\frac{1}{3}}$ and $V_l := V \setminus V_s$.
- Partition V_s into sets $(g_i)_{i=1}^k$ such that $|E|^{\frac{1}{3}} \leq \sum_{v \in g_i} \deg(v) \leq 2|E|^{\frac{1}{3}}$.
- By degree-sum, $k|E|^{\frac{1}{3}} \leq 2|E|$ so $k \leq 2|E|^{\frac{2}{3}}$.
- Any two edges incident to v can appear in at most one 4 cycle, hence the number of 4 cycles v is in is bounded by $\binom{\deg(v)}{2} \leq \frac{\deg(v)^2}{2}$
- So total number of cycles is bounded by
$$\frac{1}{2} \sum_{i=1}^k \sum_{v \in g_i} \deg(v)^2 \leq \frac{1}{2} \sum_{i=1}^k \left(\sum_{v \in g_i} \deg(v) \right)^2 \leq k4|E|^{\frac{2}{3}} \leq 4|E|^{\frac{4}{3}}$$
- By similar reasoning, $|V_l||E|^{\frac{1}{3}} \leq 2|E|$ and V_l can define at most $|E|^{\frac{4}{3}}$ cycles.

□

-  Vincent Cohen-Addad, Chenglin Fan, Euiwoong Lee, and Arnaud De Mesmay, *Fitting metrics and ultrametrics with minimum disagreements*, 2022 IEEE 63rd Annual Symposium on Foundations of Computer Science (FOCS), IEEE, 2022, pp. 301–311.
-  Chenglin Fan, Anna C Gilbert, Benjamin Raichel, Rishi Sonthalia, and Gregory Van Buskirk, *Generalized metric repair on graphs*, arXiv preprint arXiv:1908.08411 (2019).
-  Chenglin Fan, Benjamin Raichel, and Gregory Van Buskirk, *Metric violation distance: Hardness and approximation*, Algorithmica **84** (2022), no. 5, 1441–1465.
-  Anna C Gilbert and Lalit Jain, *If it ain't broke, don't fix it: Sparse metric repair*, 2017 55th Annual Allerton Conference on Communication, Control, and Computing (Allerton), IEEE, 2017, pp. 612–619.
-  Virginia Vassilevska Williams and Ryan Williams, *Subcubic equivalences between path, matrix and triangle problems*, 2010 IEEE 51st Annual Symposium on Foundations of Computer Science, 2010, pp. 645–654.