# Approximating the Held-Karp Bound for Metric TSP in Nearly Linear Time 

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## version 1

Input: clique $K_{n}$, costs $c: V \times V \rightarrow \mathbb{R}_{\geq 0}$ forming a metric

Objective:
min-cost Hamiltonian

## version 2

Input: graph $G=(V, E)$
nonnegative costs $c \in \mathbb{R}^{E}$

Objective: min-cost tour in $(G, c)$

## Metric TSP

## version 1 <br> version 2

Input: clique $K_{n}$, costs $c: V \times V \rightarrow \mathbb{R} \geq 0$ forming a metric

$$
\left.\bar{l} \overline{K_{n}}, \bar{c}\right) \text { is dense }
$$

Objective: (size $\Omega\left(\underline{n}^{2}\right)$ )
Hamiltonian min-cost Hamiltonian

Input: graph $\bar{G}=(V, E)$ nonnegative costs $c \in \mathbb{R}^{E}$

Objective:
min-cost tour in $(G, c)$

## cycle in $\left(K_{n}, c\right)$



## (Metric) Subtour Elimination

Input: clique $K_{n}=(V, E)$, metric $c: E \rightarrow \mathbb{R}_{\geq 0}$
Objective: min $\sum_{e \in E} c_{e} x_{e}$ over $x \in \mathbb{R}^{E}$

| degree <br> constraints | s.t. | $\sum_{e \in \mathscr{C}(v)} x_{e}=2$ for all vertices $v ;$ |
| :--- | :---: | :--- |
| eliminates <br> subtours | $\sum_{e \in \mathscr{C}(U)} x_{e} \geq 2$ for all sets $U \neq \emptyset, V ;$ |  |
|  | and $\mathbb{O} \leq x \leq \mathbb{1}$ |  |

## Related work (abbrev.)

- important for variants of Christofides algorithm
- solvable by ellipsoid method
- $\tilde{O}\left(n^{4} / \epsilon^{2}\right)$

Plotkin, Shmoys, Tardos [1995]

Garg and Khandekar [2004]



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## Metric TSP

## version 1 <br> version 2

Input: clique $K_{n}$, costs $c: V \times V \rightarrow \mathbb{R}_{\geq 0}$ forming a metric

Objective:
min-cost Hamiltonian
cycle in $\left(K_{n}, c\right)$

Input: graph $G=(V, E)$
nonnegative costs $c \in \mathbb{R}^{E}$

Question: $(1-\epsilon)$-APX for Held-Karp bound
in nearly-linear $\tilde{O}(m / \operatorname{poly}(\epsilon))$ time?

## Metric TSP

## version 1

## version 2

Input: clique $K_{n}$, costs $c: V \times V \rightarrow \mathbb{R}_{\geq 0}$ forming a metric

Objective:
min-cost Hamiltonian

Input: graph $G=(V, E)$ nonnegative costs $c \in \mathbb{R}^{E}$

Objective: min-cost tour in $(G, c)$ cycle in $\left(K_{n}, c\right)$

Yes: $(1-\epsilon)$-APX for Held-Karp in $\tilde{O}\left(m / \epsilon^{2}\right)$

## Held-Karp for Metric TSP

## I

## Packing cuts

## !

## Dynamic min cuts (and updates)

## 2-edge connected spanning subgraph

Input: graph $G=(V, E)$ with cuts $\mathcal{C}$
(2ECSS) nonnegative edge costs $c \in \mathbb{R}_{\geq 0}^{E}$
Objective: $\min \sum c_{e} y_{e} \quad$ over $y \in \mathbb{R}^{E}$
s.t. $\sum_{e \in \mathcal{C}}^{e \in E} y_{e} \geq 2 \quad$ for all cuts $C \in \mathcal{C}$
and $y \geq 0^{E}$
equivalent
to subtour

elimination on metric completion of $(G, c)$

## Dual of 2ECSS (2ECSSD)

Input: graph $G=(V, E)$ with cuts $\mathcal{C}$, costs $c \in \mathbb{R}_{\geq 0}^{E}$
dimension $|\mathcal{C}|$
exponential in $m$



## Dual of 2ECSS (2ECSSD)

Input: graph $G=(V, E)$ with cuts $\mathcal{C}$, dimension $|\overline{\mathcal{C}}|$ costs $c \in \mathbb{R}_{\geq 0}^{E}$
exponential
in $m$
Objective: max $2 \sum_{c(\mathbb{E} \mathcal{C})} x_{C}$ over $x \in \mathbb{R}^{\Gamma} \subset$
$\left\{\begin{array}{c}\text { \{o,1\}-packing) } \\ \text { matrix }\end{array} \sum_{C \neq e} x_{C}^{1} \leq c_{e}\right.$ for all edges $e$,


## Part 2

```
Packing cuts

\section*{Multiplicative weight updates}
cut packings \(\max \sum x_{C} \quad\) over \(x \in \mathbb{R}^{\mathcal{C}}\) st.
\[
\sum_{C \ni e}^{C \in \mathcal{C}} x_{C} \leq c_{e} \quad e \in E
\]

MWU \(>\) knapsack problems
0 initialize edge weights \(w \leftarrow 1 / c\)
1 solve relaxation \(\max \sum_{C} x_{C}\) s.t. \(x \geq \mathbb{0}\), \(\sum_{c, e: e \in c}{ }^{C} w_{e} x_{c} \leq \sum_{e} w_{e} c_{e}\)
3 output convex combination of relaxed solutions

\section*{Multiplicative weight updates}

\section*{cut packings}

MWU knapsack problems

\author{
1 solve relaxation...
}

0 initialize edge weights \(w \leftarrow 1 / c\)

1 solve relaxation \(\max \sum_{C} x_{C}\) st. \(x \geq 0\),

\(\tilde{O}\left(m / \epsilon^{2}\right)\) iterations
2 for each \(e \in E\)
\[
w_{e} \leftarrow \exp \left(\frac{\epsilon \sum_{C \ni \ni} \frac{x_{C}}{c_{C}}}{\max _{h} \sum_{C \ni h} \frac{x_{C}}{c_{h}}}\right) w_{e}
\]

\section*{Multiplicative weight updates}

\section*{cut packings}

MWU \(>\) knapsack problems
1) solve relaxation...
a \(C \leftarrow \min -\operatorname{cut}(G, w)\)
Ô(m) time [Karger]
b \(x \leftarrow \frac{\langle w, c\rangle}{\sum_{e \in T} w_{e}} e_{T}\)

0 initialize edge weights \(w \leftarrow 1 / c\)
1 solve relaxation \(\max \sum_{C} x_{C}\) s.t. \(x \geq \mathbb{0}\), \(\sum_{c, e: e \in c}{ }^{C} w_{e} x_{c} \leq \sum_{e} w_{e} c_{e}\)
\(\tilde{O}\left(m / \epsilon^{2}\right)\) iterations
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\]

\section*{Multiplicative weight updates}

\section*{cut packings}

\section*{min-weight cuts}

2 for each \(e \in E\) \(w_{e} \leftarrow \exp \left(\frac{\epsilon \sum_{C \ni e} \frac{x_{C}}{c_{e}}}{\max _{h} \sum_{C \ni h} \frac{x_{C}}{c_{h}}}\right) w_{e}\)

0 initialize edge weights \(w \leftarrow 1 / c\)
a \(C \leftarrow \min -\operatorname{cut}(G, w)\)
\(\hat{O}(m)\) time [Karger \(]\)
b \(x \leftarrow \frac{\langle w, c\rangle}{\sum_{e \in T} w_{e}} e_{T}\)
\(\tilde{O}\left(m / \epsilon^{2}\right)\) iterations
2 for each \(e \in E\)
\[
w_{e} \leftarrow \exp \left(\frac{\left.\epsilon \sum_{C \ni \exists} \frac{\frac{x_{C}}{e_{e}}}{\max _{h} \sum_{C \ni h} \frac{x_{C}}{c_{h}}}\right) w_{e} .}{}\right.
\]

\section*{Multiplicative weight updates}

\section*{cut packings}

\section*{min-weight cuts}

2 for each \(e \in E\) \(w_{e} \leftarrow \exp \left(\frac{\epsilon \sum_{C \ni e} \frac{x_{C}}{c_{e}}}{\max _{h} \sum_{\subsetneq \ni h} \frac{x_{C}}{c_{h}}}\right) w_{e}\)
\(\Rightarrow\) for each \(e \in C\),
\(w_{e} \leftarrow\)
\[
\exp \left(\frac{\epsilon \min _{h \in C} c_{h}}{c_{e}}\right) w_{e}
\]

0 initialize edge weights \(w \leftarrow 1 / c\) a \(C \leftarrow \min -\operatorname{cut}(G, w)\) \(\hat{O}(m)\) time [Karger \(]\) \(\sum_{e \in T} w_{e} e_{T}\)
\(\tilde{O}\left(m / \epsilon^{2}\right)\) iterations
2 for each \(e \in E\)
\[
w_{e} \leftarrow \exp \left(\frac{\left.\epsilon \sum_{C \ni \ni} \frac{\frac{x_{C}}{c_{e}}}{\max _{h} \sum_{C \ni h} \frac{x_{C}}{c_{h}}}\right) w_{e} .}{}\right.
\]

\section*{Multiplicative weight updates}
cut packings

\section*{min-weight cuts}


\section*{Multiplicative weight updates}

\section*{cut packings \\ min-weight cuts}

2 bottlenecks

0 initialize edge weights \(w \leftarrow 1 / c\)

\section*{a \(C \leftarrow \min -\operatorname{cut}(G, w)\) \\ O\(O(m)\) time [Karger]}
b \(x \leftarrow \frac{\langle w, c\rangle}{\sum_{e \in T} w_{e}} e_{T}\)
\(\tilde{O}\left(m / \epsilon^{2}\right)\) iterations
2 for \(e \in C, w_{e} \leftarrow\)
\[
\exp \left(\frac{\epsilon \min _{h \in C} c_{h}}{c_{e}}\right) w_{e}
\]

\section*{Multiplicative weight updates}

\section*{cut packings}

\section*{MWU}
min-weight cuts
a \(C \leftarrow \min -\operatorname{cut}(G, w)\)
\(\tilde{O}(m)\) per min cut
\(\times \tilde{O}\left(m / \epsilon^{2}\right) \quad\) iterations
\(\approx \tilde{O}\left(m^{2} / \epsilon^{2}\right)\) running time

2 for \(e \in C, w_{e} \leftarrow \cdots\) \(\Omega(m) \quad\) edge updates per cut \(\times \tilde{O}\left(m / \epsilon^{2}\right) \quad\) iterations
\(\tilde{O}\left(m^{2} / \epsilon^{2}\right)\) running time

0 initialize edge weights \(w \leftarrow 1 / c\)


\title{
From \(\tilde{O}\left(m^{2} / \epsilon^{2}\right)\) to \(\tilde{O}\left(m / \epsilon^{2}\right)\)
} min-cut oracle
what we have
\(\tilde{O}(m)\) per min cut
what we need
\(\tilde{O}(1)\) amor. per \((1+\epsilon)\)-apx min-cut
weight update
\(\Omega(m)\) edges per cut
additional • no suitable dynamic data structures challenges • min-cut varies dramatically between iterations


Karger's \(\tilde{O}(m)\) min-cut algorithm
1. Randomly contract edge. Repeat.

\section*{Karger's \(\tilde{O}(m)\) min-cut algorithm}
1. Randomly contract edge. Repeat.
1. Pack spanning trees
2. Randomly sample \(O(\log n)\) trees
3. Search each sampled tree for min-cut induced by 1 or 2 edges by dynamic programming

Tree packings and network strength
Input: graph \(G=(V, E) \mathrm{w} /\) spanning trees \(\mathcal{T}\) and positive edge capacities \(c \in \mathbb{R}^{E}\)
Objective: \(\max \sum_{T \in \mathcal{T}} x_{t}\) over \(x \in \mathbb{R}^{\mathcal{T}}\)
\[
\begin{aligned}
& \text { s.t. } \sum_{T \ni e} x_{T} \leq c_{e} \text { for each edge } e \\
& \\
& x \geq \mathbb{O}^{\mathcal{T}}
\end{aligned}
\]
\((1-\epsilon)\)-apx tree packings in \(\tilde{O}(m)\) time via either:
- sparsification [Karger 00] - MWU [CQ SODA17]

Tree packings and network strength Input: graph \(G=(V, E) \mathrm{w} /\) spanning trees \(\mathcal{T}\) and positive edge capacities \(c \in \mathbb{R}^{E}\)

Objective: \(\max \sum_{T \in \mathcal{T}} x_{t}\) over \(x \in \mathbb{R}^{\mathcal{T}}\)
s.t. \(\sum_{T \ni e} x_{T} \leq c_{e}\) for each edge \(e\)
\[
x \geq \mathbb{0}^{\mathcal{T}}
\]


\title{
Tutte; Nash-Williams;
}

Undirected graph w/ min cut \(\kappa\) has a tree packing of value \(\geq \kappa / 2\)

\begin{tabular}{l} 
Tote: Nash -Williams: \\
\hdashline Undirected graph w/ min cut \(\kappa\) has
\end{tabular} a tree packing of value \(\geq \kappa / 2\)
0 let \(P\) be a \((1-\epsilon)\)-apx max tree packing \(C\) be a \((1+\epsilon)\)-ap min cut
1 each edge \(e \in C\) is in a tree \(T \in P\)
2 avg \# \(C\)-edges per tree
\[
=\frac{|C|}{|P|} \leq \frac{(1+\epsilon) \kappa}{(1-\epsilon) \kappa / 2}=2+O(\epsilon)
\] trees have \(<3 C\)-edges

\section*{Karger's \(\tilde{O}(m)\) min-cut algorithm}
1. Randomly contract edge. Repeat.
1. Pack spanning trees
2. Randomly sample \(O(\log n)\) trees
3. Search each sampled tree for min-cut induced by 1 or 2 edges by dynamic programming

Fix a rooted tree \(T \Rightarrow\) poset on \(V\)

" \(u<v\) " means \(u\) is a descendant of \(v\)
" \(v \| w\) " means \(v\) and \(w\) are incomparable
" \(D(x)\) " means all descendants of \(x\)


\section*{2 incomparable 2-cut}
 (where \(s \| t\) ) \(\quad \underset{C}{ }(D(t) \backslash D(s))\)
\((\mathscr{C}(S)=\) edges cut by \(S)\)

(where \(s \leq t\) )


\section*{2-cuts are a little more complicated...}


\section*{Link-Cut trees}
(a) add along \(v \rightarrow\) root path (b) get min over \(v \rightarrow\) root path in \(\tilde{O}(1)\) time 1. init each \(v\) to \(\overline{\mathscr{C}}(D(v))\)
2. add \(\infty\) to all \(v>s\)
3. for each \(e=(s, v)\)
a. subtract \(2 w(e)\) from
all \(u \geq v\)
4. for each \(e=(s, v)\)
a. find min value over
all \(u \geq v\)

incomparable 2-cut with a path to a leaf
\[
\begin{aligned}
& \overline{\mathscr{C}}(D(t))-2 \overline{\mathscr{C}}\left(D\left(s_{i}\right), D(t)\right) \\
& \text { already }-1 \\
& \text { computed }
\end{aligned}
\]
\(\overline{\mathscr{C}}\left(D\left(s_{i}\right), D(t)\right)=\)
\[
\overline{\mathscr{C}}\left(D\left(s_{i-1}\right), D(t)\right)+\overline{\mathscr{C}}\left(s_{i}, D(t)\right)
\]
consecutive \(D\left(s_{i}\right)\) are closely related
 \(\tilde{O}\left(\operatorname{deg}\left(s_{1}, \ldots, s_{\ell}\right)\right)\)
1. process \(s_{1}\) like a leaf
2. for \(i=2, \ldots, \ell\)
a. keep aggr. values from \(s_{i-1}\)
b. process edges incident
to \(s_{i}\) like a leaf
3. return best min over all \(i\)induction step

1. process each path
to a leaf
2. contract each path into its parent
3. recurse
each leaf in new graph had \(\geq 2\) children before \(\Downarrow\)
number of nodes
is halved


\section*{2-cuts are a little more complicated...}


\section*{reduces to dynamic programming with dynamic trees}


\section*{Incremental setting}
- edge weights incremented online (adversarially)
- need to maintain \((1+\epsilon)\)-apx min cut

\section*{Incremental Karger’s algorithm}
- initially: \(\lambda \leftarrow\) initial value of min-cut,
pack and sample \(\log n\) spanning trees
- when we need an apx min-cut:
- continue Karger's search until we find a cut of value \(\leq(1+\epsilon) \lambda\), output and pause the search
- if good cut not found, then re-pack/sample trees
- when we increment an edge weight
- incorporate into tree sums w/ dynamic trees

\section*{From \(\tilde{O}\left(m^{2} / \epsilon^{2}\right)\) to \(\tilde{O}\left(m / \epsilon^{2}\right)\)}
min-cut oracle
what we
have
\(\tilde{O}(m)\) per min cut
\(\tilde{O}(1)\) amor. per \((1+\epsilon)\)-ap min-cut
what we need
weight update
\(\Omega(m)\) edges per cut
\(\tilde{O}(1)\)
amortized
time per cut
what we \(\tilde{O}\left(m / \epsilon^{2}\right)\) total time get \(+\tilde{O}(1)\) per min cut ?? \(+\tilde{O}(1)\) per edge inc

\section*{Updating edge weights along cuts}
- need to update weights of all edges in a cut
- we know how to update fixed sets efficiently [Young '14, Chekuri-Q SODA17]
- problem: cuts vary dramatically between iterations
- key point: all cuts are induced by trees

- this decomposes each 1,2-cut to \(\log ^{2} n\) "canonical cuts" between canonical subtrees

\section*{Updating edge weights along cuts}
- need to update weights of all edges in a cut
we know how to update fixed sets efficiently
[Young '14, Chekuri-Q SODA17]
- problem: cuts vary dramatically between iterations
- key point: all cuts are induced by trees
"canonical cuts" with total size \(\tilde{O}(m)\)
\(\hat{\hbar}+\hat{\hbar}=>\log ^{2} n\) efficient updates on fixed sets

\section*{\(\operatorname{From} \tilde{O}\left(m^{2} / \epsilon^{2}\right)\) to \(\tilde{O}\left(m / \epsilon^{2}\right)\)}
min-cut oracle
what we have
\(\tilde{O}(m)\) per min cut
what we
\(\tilde{O}(1)\) amor. per need \((1+\epsilon)\)-apx min-cut
weight update
\(\Omega(m)\) edges per cut
\(\tilde{O}(1) \quad\) amortized time per cut
\(\tilde{O}\left(m / \epsilon^{2}\right)\) init time
\(+\tilde{O}(1)\) per min cut
\(+\tilde{O}\left(m / \epsilon^{2}\right) \quad\) edge
increments


The main result. In this paper we obtain a near-linear running time for a ( \(1+\epsilon\) )-approximation, substantially improving the best previously known running time bound.

Theorem 1.1. Let \(\mathcal{G}=(\mathcal{V}, \mathcal{E})\) be an undirected graph with \(|\mathcal{E}|=m\) edges and \(|\mathcal{V}|=n\) vertices, and positive edge weights \(c: \mathcal{E} \rightarrow \mathbb{R}_{>0}\). For any fixed \(\epsilon>0\), there exists a randomized algorithm that computes a \((1+\epsilon)\)-approximation to the Held-Karp lower bound for the Metric-TSP instance on \((\mathcal{G}, c)\) in \(O\left(m \log ^{4} n / \epsilon^{2}\right)\) time. The algorithm succeeds with high probability.

The algorithm in the preceding theorem can be modified to return a \((1+\epsilon)\)-approximate solution to the 2ECSS LP within the same asymptotic time bound. For fixed \(\epsilon\), the running time we achieve is asymptotically faster than the time to compute or even write down the metric completion of \((\mathcal{G}, c)\). Our algorithm can be applied low-dimensional geometric point sets to obtain a running-time that is near-linearly in the number of points.

In typical approximation algorithms that rely on mathematical programming relaxations, the bottleneck for the running time is solving the relaxation. Surprisingly, for algorithms solving MetricTSP via the Held-Karp bound, the bottleneck is no longer solving the relaxation (albeit we only find a ( \(1+\epsilon\) )-approximation and do not guarantee a basic feasible solution). We mention that the recent approaches towards the \(4 / 3\) conjecture for Metric-TSP are based on variations of the classical Christofides heuristic (see [Vygen, 2012]). The starting point is a near-optimal feasible solution \(x\) to the 2ECSS LP on \((\mathcal{G}, c)\). Using a well-known fact that a scaled version of \(x\) lies in the spanning tree polytope of \(\mathcal{G}\), one generates one or more (random) spanning trees \(T\) of \(\mathcal{G}\). The tree \(T\) is then augmented to a tour via a min-cost matching \(M\) on its odd degree nodes. Genova and Williamson [2017] recently evaluated some of these Best-of-Many Christofides' algorithms and demonstrated


\section*{Christofides' heuristic [1976] (Recent work)}
- simple (\& best) 3/2-approximation for metric TSP
- bottlenecks include all-pairs shortest paths, min-cost perfect matching on dense graph
- \((1+\epsilon)-\mathrm{apx}\) to \(2 \mathrm{ECSS}=>\)
\((1+\epsilon) \frac{3}{2}\)-apx in \(\tilde{O}\left(n^{1.5} / \epsilon^{3}\right)\) time
- \(=>\tilde{O}\left(m / \epsilon^{2}+n^{1.5} / \epsilon^{3}\right)\) time total

Thanks!```

