## Approximating TSP

## Admin

- "Assignment 10" (optional) review times:
- Tuesday 9-11am
- Wednesday 1-3pm
- Thursday 3:30-5:30pm
- Friday 3-5pm
- TAs have office hours if you have any general questions
- I did give them the assignment 10 solutions but they may not be as familiar as they would be
- Any questions?


## Greedy is a 2-Approximation

- Proof.
- Consider load $L(i)$ of bottleneck machine $i$
- $L[i]-t_{j} \leq$ OPT
- We know that $t_{j} \leq$ OPT
- Thus, $L=L[i] \leq \mathrm{OPT}+t_{j}$ $\leq 2 \mathrm{OPT}$



## Greedy is a 2-Approximation

- Is our analysis tight?
- Close to it.
- Consider $m(m-1)$ jobs of length 1 and 1 job of length $m$
- How would greedy schedule these jobs?
- Greedy will evenly divide the first $m(m-1)$ jobs among $m$ machines, will place the final long job on any one machine
- Makespan: $m-1+m=2 m-1$
- How would optimal schedule it?
- Give the long job to one machine, the rest split the other small jobs with a makespan $m$
- Ratio: $(2 m-1) / m \approx 2$


## Greedy is Online

- Notice that our greedy algorithm is an online algorithm
- Assigns jobs to machines in the order they arrive
- Does not depend on future jobs
- Can we do better, if we assume all jobs are available at start time?
- Offline. Slight modification of greedy gets better approximation!


## Improving on Online Greedy

- Worst case of our greedy algorithm: spreading jobs out evenly when a giant job at the end messed things up
-What can we do to avoid this?
- Idea: deal with larger jobs first
- Small jobs can only hurt so much
- Turns out this improves our approximation factor
- Longest-processing-time (LPT) first. Sort $n$ jobs in decreasing order of processing times; then run the greedy algorithm on them
- Claim. LPT has a makespan at most 1.5 - OPT
- Observation. If we have fewer than $m$ jobs, then the greedy solution is clearly optimal (as it puts each job on its own machine)


## LPT-first is a 1.5-Approximation

- Lemma. LPT-first has a makespan at most $1.5 \cdot$ OPT
- Observation.
- If we have fewer than $m$ jobs, then the greedy solution is clearly optimal (as it puts each job on its own machine)
- Claim. If more than $m$ jobs then, OPT $\geq 2 \cdot t_{m+1}$
- Proof. Consider the first $m+1$ jobs in sorted order.
- They each take at least $t_{m+1}$ time
- $m+1$ jobs and $m$ machines, there must be a machine with at least two jobs
- Thus the optimal makespan OPT $\geq 2 \cdot t_{m+1}$


## LPT-first is a 1.5-Approximation

- Lemma. LPT-first has a makespan at most $1.5 \cdot$ OPT
- Proof. Similar to our original proof. Consider the machine $M_{i}$ that has the maximum load
- If $M_{i}$ has a single job, then our algorithm is optimal
- Suppose $M_{i}$ has at least two jobs and let $t_{j}$ be the last job assigned to the machine, note that $j \geq m+1$ (why?)
- Thus, $t_{j} \leq t_{m+1} \leq \frac{1}{2}$ OPT



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- $L[i]-t_{j} \leq$ OPT
. $L[i] \leq \frac{3}{2}$ OPT



## Is our 1.5-Approximation tight?

- Question. Is out $3 / 2$-approximation analysis tight?
- Turns out, no
- Theorem [Graham 1969]. LPT-first is a 4/3-approximation.
- Proof via a more sophisticated analysis of the same algorithm
- Question. Is the 4/3-approximation analysis tight?
- Pretty much.
- Example
- $m$ machines, $n=2 m+1$ jobs
- 2 jobs each of length $m, m+1, \ldots, 2 m-1+$ one job of length $m$
- Approximation ratio $=(4 m-1) / 3 m \approx 4 / 3$


## Can we do better than $4 / 3$ ?

- Long series of improvements
- Polynomial time algorithm for any constant approximation [Hochbaum Shmoys 87]
- Specifically: $(1+\epsilon)$ approximation in $O\left((n / \epsilon)^{1 / \epsilon^{2}}\right)$ time
- PTAS: Polynomial time approximation scheme
- For any desired constant-factor approximation, there exists a polynomial-time algorithm

Approximate TSP

## Approximating TSP

- Recall the traveling salesman problem
- $n$ cities labeled $v_{1}, \ldots, v_{n}$
- Let $d(i, j)$ be the distance from city $v_{i}$ to city $v_{j}$
- TSP. (Decision Version) Given pairwise distance between $n$ cities and a bound $D$, is there a tour (that visits each city exactly once and returns to starting city) of length at most $D$ ?
- NP complete problem. Reduction from Hamiltonian cycle.
- Given directed graph $G=(V, E)$, define instance of TSP as:
- City $c_{i}$ for each node $v_{i}$
- $d\left(c_{i}, c_{j}\right)=1$ if $\left(v_{i}, v_{j}\right) \in E$
- $d\left(c_{i}, c_{j}\right)=2$ if $\left(v_{i}, v_{j}\right) \notin E$


## Bad News: Approx-TSP is hard

- Claim. There is no polynomial-time $c$-approximation algorithm for the general TSP problem, for any constant $c \geq 1$, unless $\mathrm{P}=\mathrm{NP}$.
- Proof. Suppose there is a poly-time $c$-approximation algorithm $A$ that computes a TSP tour of total weight at most $c \cdot$ OPT
- Show that $A$ can be used to solve the Hamiltonian cycle problem
- Modified reduction from Hamiltonian cycle instance $G$ to TSP instance:
- $d\left(c_{i}, c_{j}\right)=1$ if $\left(v_{i}, v_{j}\right) \in E$
- $d\left(c_{i}, c_{j}\right)=c n+1$ if $\left(v_{i}, v_{j}\right) \notin E$
- If $G$ has a Hamiltonian cycle: there is a tour of length exactly $n$
- If $G$ does not have a Hamiltonian cycle, any tour has length at least $c n+1$


## Bad News: Approx-TSP is hard

- Claim. There is no polynomial-time $c$-approximation algorithm for the general TSP problem, for any constant $c \geq 1$, unless $\mathrm{P}=\mathrm{NP}$.
- Proof. (Cont)
- If $G$ has a Hamiltonian cycle: there is a tour of length exactly $n$
- If $G$ does not have a Hamiltonian cycle, any tour has length at least $c n+1$
- A computes tour of length at most $c n \Longleftrightarrow G$ has a Hamiltonian cycle: $A$ solves Hamiltonian cycle in polynomial time and $P=N P$
- [More Bad news]

For any function $f(n)$ that can be computed in polynomial time in $n$, there is no polynomial-time $f(n)$-approximation for TSP on general weighted graphs, unless $\mathrm{P}=\mathrm{NP}$.

## Good News: Metric TSP is Not

- While approximating TSP on general distances is NP hard, the common special case can be approximate easily
- Metric TSP. TSP problem where the distances satisfy the triangle inequality, that is,
- $d(i, j) \leq d(i, k)+d(k, j)$ for any cities $i, j, k$
- Other properties of Euclidean (metric) distances:
- $d(i, i)=0$ and $d(i, j) \geq 0$ [Identify and Non-negative]
- $d(i, j)=d(j, i)$ [Symmetric]
- Note that Metric TSP is still NP complete (reduction from undirected hamiltonian cycle)
- Setting $d\left(c_{i}, c_{j}\right)=2$ when $\left(v_{i}, v_{j}\right) \notin E$ satisfies triangle inequality


## Approximating Metric TSP

- Consider the weighted complete graph $G$ where each vertex is a city, and each edge $(i, j)$ for $i, j \in V$ has weight equal to the distance $d(i, j)$, where $d$ satisfies the triangle inequality
- To approximate, consider the optimization version of the problem
- Goal. Find the tour of min total distance that visits each city once
- Steps to follow when designing an approximation algorithm for a minimization problem (NP hard)?
- Lower bound the optimal cost by some function of input
- Upper bound the cost of algorithm by the same function
- Minimum spanning trees give us such upper/lower bounds
- We give a 2 -approximation to metric-TSP using minimum
spanning trees


## Lower Bound on OPT

- Claim. Let $T$ be the minimum spanning tree of $G$ then length of the optimal tour OPT $\geq w(T)$.
- Proof
- Take an optimal tour of length OPT
- Drop an edge from it to obtain a spanning tree $T^{\prime}$
- Distances/weights are non-negative, so $w\left(T^{\prime}\right) \leq$ OPT
- $w(T) \leq w\left(T^{\prime}\right) \quad(T$ is the MST)
- Thus $w(T) \leq$ OPT



## Double Tree Algorithm

- Find a minimum spanning tree $T$
- Duplicate every edge in $T$
- Find an Eulerian tour of resulting multi-graph
- Shortcut Euler tour to avoid repeated vertices



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Why must an Euler tour exist?


A,B,D,H,D,I,D,B,E,B,F,B,A,C,G,C,A

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$\mathrm{A}, \mathrm{B}, \mathrm{D}, \mathrm{H}, \mathrm{Q}, \mathrm{I}, \Xi, \mathrm{B}, \mathrm{E}, \mathrm{B}, \mathrm{F}, \mathrm{B}, \mathrm{A}, \mathrm{C}, \mathrm{G}, \mathrm{C}, \mathrm{A}$


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## Double Tree Analysis

- Claim. The double-tree algorithm is a 2-approximation to TSP.
- Proof. The Euler tour visits every edge of MST $T$ exactly twice, thus the length of tour $\leq 2 \cdot w(T)$
- Due to triangle inequality, shortcutting the tour does not increase length
- Since $w(T) \leq$ OPT, we get that our tour length is $\leq 2$. OPT




## Christofides Algorithm [Christofides 76][Serdyukov 76]

- Doubling the edges of MST is one way to obtain Euler tour of the MST, but is there a cheaper way to augment to tree to obtain an Eulerian tour?
- A graph has an Euler tour iff all nodes have even degree
-What is the parity of odd degree vertices in an undirected graph?
- Even number of odd degree vertices!
- Christofides algorithm. Starts with an MST, but fixes the parity of odd degree vertices by augmenting it with a matching
- Matching. A set of edges such that no two are adjacent
- Perfect matching. Every vertex is incident to exactly one edge in the matching
- Fact We'll Use. Minimum cost "perfect" matchings of any graph can be computed in polynomial time.


## Minimum Cost Matching

- Won't see in this class, unfortunately
- Edmond's "blossom" algorithm
- $O\left(|E||V|^{2}\right)$ (slow, but much better than exponential)
- Somewhat similar to Ford-Fulkerson:
- Use special structure to prove that we just need to find augmenting paths

- Use data structures so that we can find augmenting paths quickly
- Tricky part: "augmenting paths" are more complicated when finding a matching



## Christofides Algorithm

- Find the minimum spanning tree $T$
- Compute $O$ : the set of odd degree vertices in $T$
- Find the min-cost perfect matching $M$ of subgraph induced

All odd-degree vertices and any edges connecting them

- Return shortcut of Euler tour of $T \cup M$



## Christofides Algorithm

- Find the minimum spanning tree $T$
- Compute $O$ : the set of odd degree vertices in $T$
- Find the min-cost perfect matching $M$ of subgraph induced

What does adding $M$ do to $O$ ?

- Return shortcut of Euler tour of $T \cup M$



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## Christofides Analysis

- Cost of TSP tour returned is at most $w(T)+w(M)$
- We know OPT $\geq w(T)$
- To bound the approximation factor, we lower bound the OPT in terms of the cost of $M$
- Claim. Let OPT be the length of the optimal tour and let $M$ be a minimum-cost perfect matching on the complete subgraph induced by $O$, the odd degree nodes in MST $T$, then

$$
w(M)=\sum_{e \in M} w_{e} \leq \frac{1}{2} \cdot \mathrm{OPT}
$$

- Once we prove the lemma, we have, $w(T)+w(M) \leq \frac{3}{2}$. OPT
- Thus, Christofides algorithm is a 3/2-approximation to metric TSP


## Christofides Analysis

- Proof of claim. Consider an optimal tour with cost OPT and consider vertices in $O$, the odd-degree vertices in $T$
- Shortcut optimal tour to obtain tour of vertices in $O$
- By triangle inequality the cost of tour can only decrease



## Christofides Analysis

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- Shortcut optimal tour to obtain tour of vertices in $O$
- By triangle inequality the cost of tour can only decrease
- Consider matchings $M_{1}, M_{2}$ created by alternating edges on this tour
- $w\left(M_{1}\right)+w\left(M_{2}\right) \leq$ OPT
- Then, $\min \left\{w\left(M_{1}\right), w\left(M_{2}\right)\right\} \leq \mathrm{OPT} / 2$
- $w(M) \leq \min \left\{w\left(M_{1}, w\left(M_{2}\right)\right\}\right.$, where $M$ :min-cost perfect matching on subgraph induced by $O$
- Thus, $w(M) \leq$ OPT/2


## TSP: Summary

- Held \& Karp [1970s] developed a hueristic for calculating a lower bound on a TSP tour (coincides with a linear program known as Held-Karp relaxation)
- Conjectured to give a 4/3-approximation
- [Papadimitriou \& Vempala, 2000's] NP-hard to approximate metric TSP within 220/219~1.0004
- Simplified and slightly improved by Lampis'12
- "Four decades after its discovery, Christofedes' algorithm is the best approximation algorithm known for metric TSP"

Christofide's isn't optimal!

- This past summer [Karlin, Klein, Shayan] (unpublished):
- 1.499999999999999999999999999999999999 approximation
- "Euclidean TSP" does have a PTAS! [Aurora 98] [Mitchell 99]
- Understanding the approximability of TSP is a major open problem in TCS


## Acknowledgments

- Some of the material in these slides are taken from
- Kleinberg Tardos Slides by Kevin Wayne (https:// www.cs.princeton.edu/~wayne/kleinberg-tardos/pdf/ 04GreedyAlgorithmsl.pdf)
- Jeff Erickson's Algorithms Book (http://jeffe.cs.illinois.edu/teaching/ algorithms/book/Algorithms-JeffE.pdf)
- Lecture slides: https://web.stanford.edu/class/archive/cs/cs161/ cs161.1138/

