

On Approximability of Bounded Degree Instances of Selected Optimization Problems

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Ph.D. Thesis Defense
July 25, 2013

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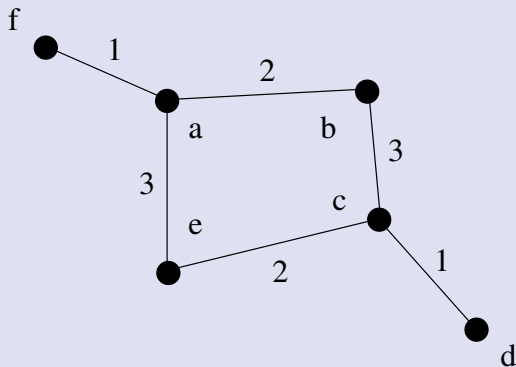
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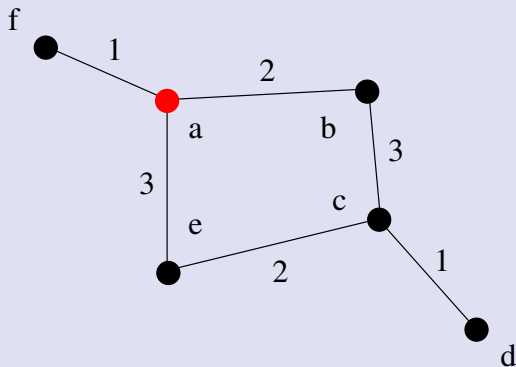
- **Traveling Salesman Problem (TSP)**
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An instance of the Metric TSP (shortest-path metric)

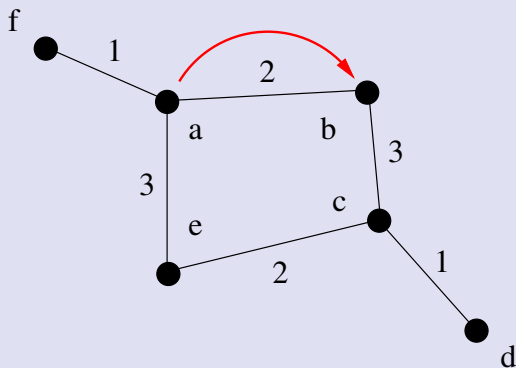


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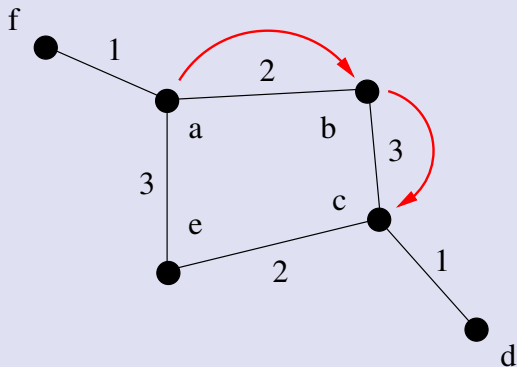
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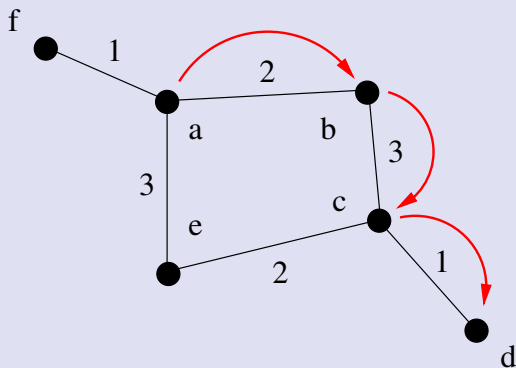
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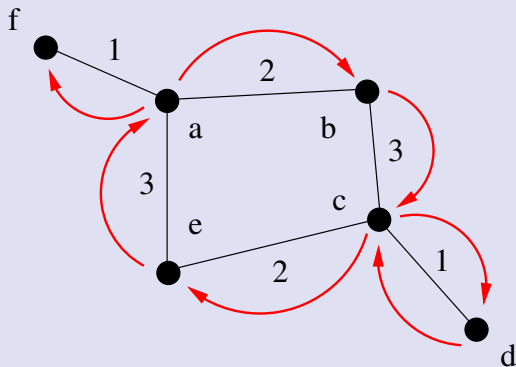
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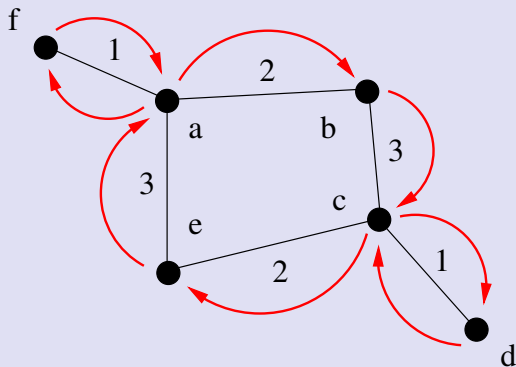
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Objective: Find an ordering of the points v_1, v_2, \dots, v_n such that $d(v_1, v_2) + d(v_2, v_3) + \dots + d(v_n, v_1)$ is minimized

The Metric TSP

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- APX-hard [Papadimitriou & Yannakakis'93]
- First explicit inapproximability bound: $5381/5380$ [Engebretsen'00]

Explicit inapproximability constants for the Metric TSP

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Theorem (Karpinski, Lampis & S.'13)

It is NP-hard to approximate the Metric TSP within any factor less than 123/122.

The Reduction (Metric TSP)

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Starting point: Inapproximability result for MAX-E3LIN2

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Definition (MAX-E3LIN2)

Input: A system \mathcal{L} of linear equations mod 2, in which equations are of the form $x_i \oplus x_j \oplus x_k = b$ with $b \in \{0, 1\}$

Output: An assignment to the variables in \mathcal{L} that maximizes the number of satisfied equations

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Approximation lower bound: MAX-E3LIN2 is NP-hard to approximate to within any factor less than 2. [Håstad'01]

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High-level view of the reduction:

- Construct a reduction from MAX-E3LIN2 to Metric TSP ($\mathcal{L} \rightarrow$ TSP instance)

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High-level view of the reduction:

- Construct a reduction from MAX-E3LIN2 to Metric TSP ($\mathcal{L} \rightarrow$ TSP instance)
- Reduction is easier if the number of occurrences of each variable in \mathcal{L} is bounded by a constant (to control the consistency of variable gadgets)

The Reduction (Metric TSP)

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- → We need inapproximability results for MAX-E3LIN2 with bounded number of occurrences of variables

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 - Prove our result for Metric TSP

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Definition (Strong expander)

A graph $G = (V, E)$ is a **strong expander** if for all $S \subseteq V$ with $|S| \leq |V|/2$, we have that $|\{e \in E \mid |e \cap S| = 1\}| \geq |S|$.

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Note: $x \oplus y = 0$ if and only if $x = y$ (**equality equation**)

Optimal assignments are consistent

- 1 Suppose that in the new instance the optimal assignment sets some of the x_i 's to **0** and others to **1** \rightarrow partition of the strong expander

2

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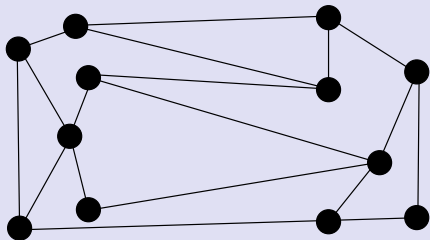
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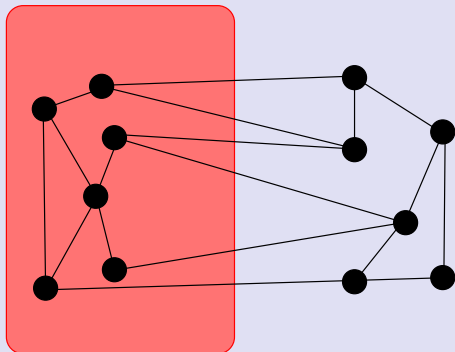
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- 3 This gives some inapproximability factor

Unfortunately:

For $\Delta < 6$, strong expander are yet **not known to exist!**

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Amplifier graphs

- **Amplifier graphs** are strong expander graphs for a certain subset of vertices (**contact vertices**)
- The other vertices are thrown in to make consistency easier to achieve (**checker vertices**)
- This allows us to get smaller Δ

Special class of amplifier graphs with $\Delta = 3$:

Wheel amplifier graphs [Berman & Karpinski'99]

Construction:

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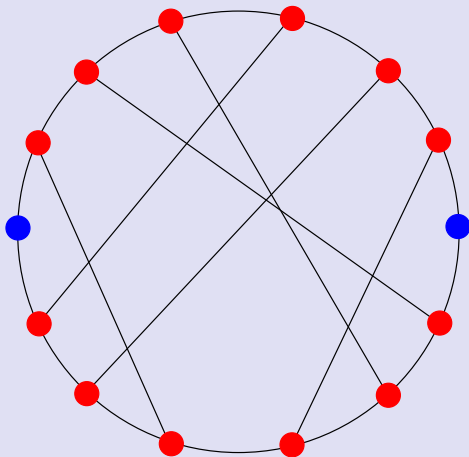
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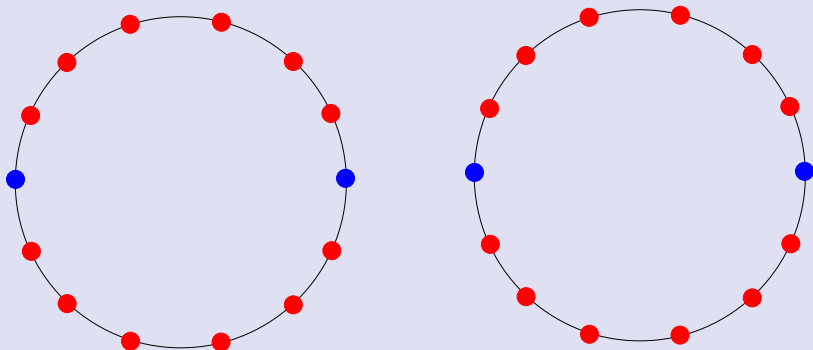
- Start with a cycle on $7n$ vertices
- Every seventh vertex is a **contact vertex**
- Other vertices are **checker vertices**
- There is a perfect matching on the set of checker vertices

Wheel amplifier graph



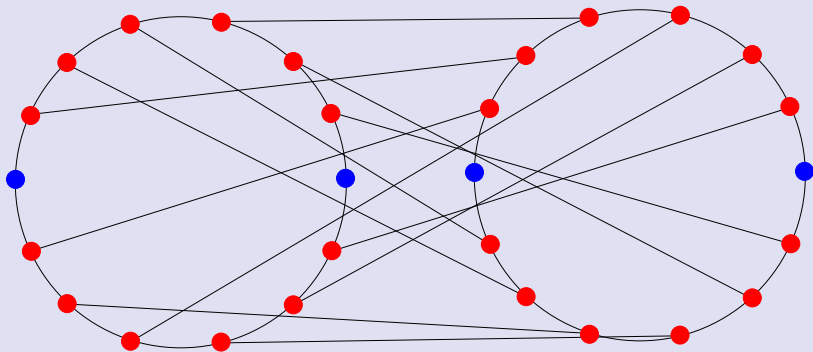
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Note: $x \oplus y = 1$ if and only if $x \neq y$ (inequality equation)

The Reduction (Metric TSP) cont'd

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Construction ($\mathcal{L}_{3OCC} \rightarrow$ TSP instance):

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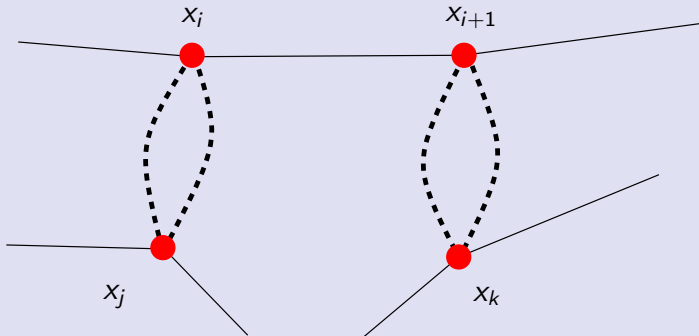
Given an instance \mathcal{L}_{3OCC} ,

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- Add gadgets for equations with 3 variables (containing the contact vertices)

The Reduction (Metric TSP)

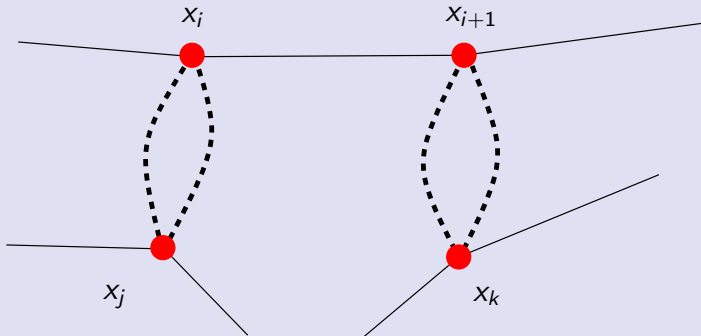
Forced edge: any tour is forced to use this edge at least once

Inequality gadgets for $x_i \oplus x_j = 1$ and $x_{i+1} \oplus x_k = 1$



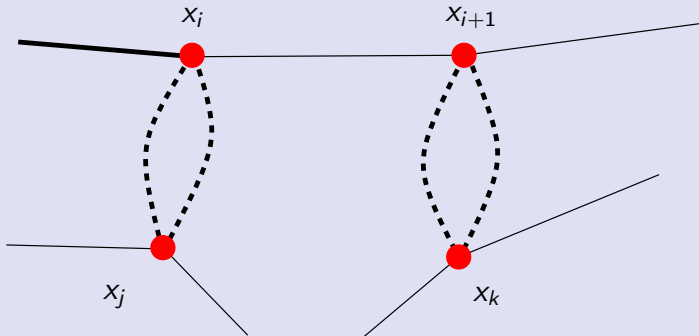
The Reduction (Metric TSP)

Simulating $x_i \oplus x_{i+1} = 0$, $x_i \oplus x_j = 1$ and $x_{i+1} \oplus x_k = 1$



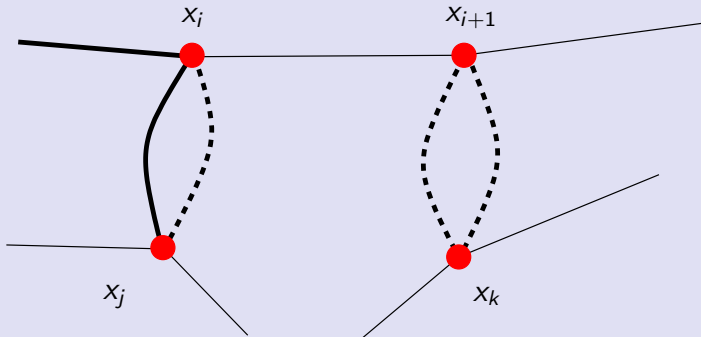
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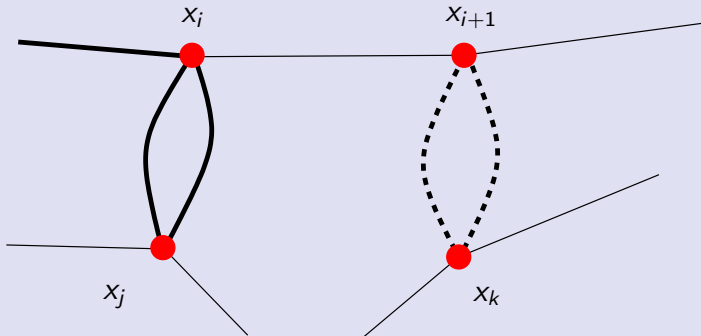
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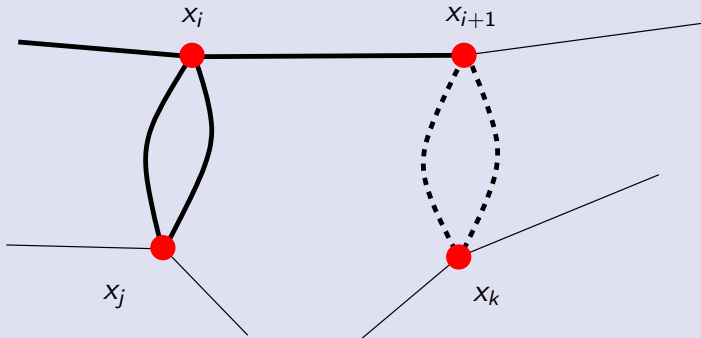
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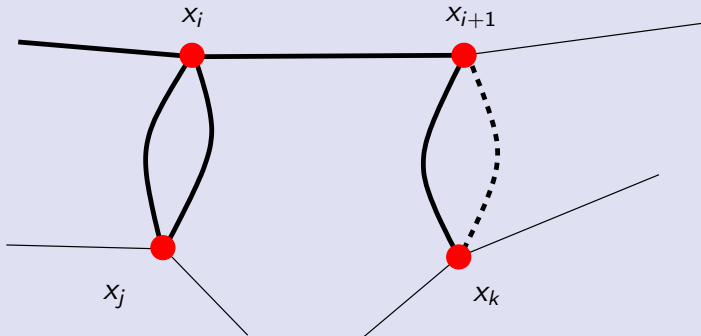
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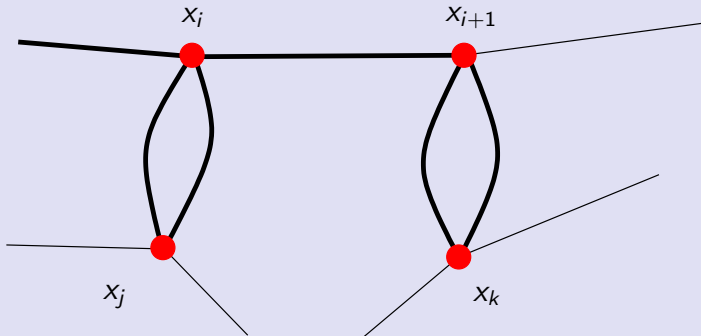
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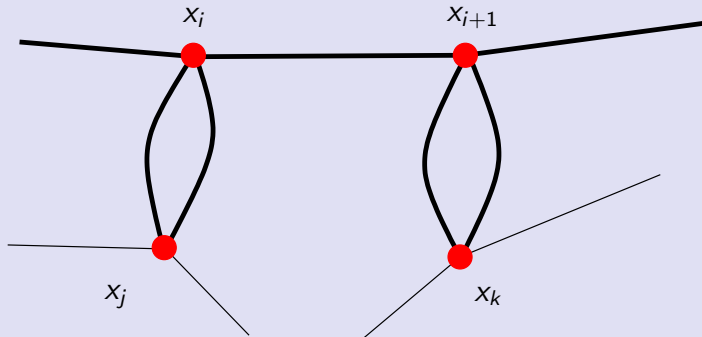
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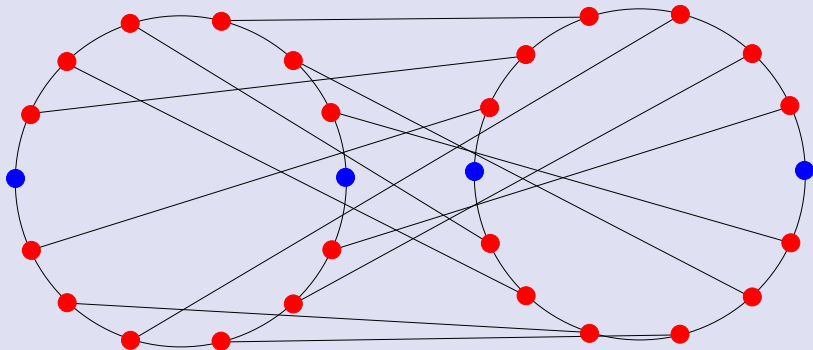
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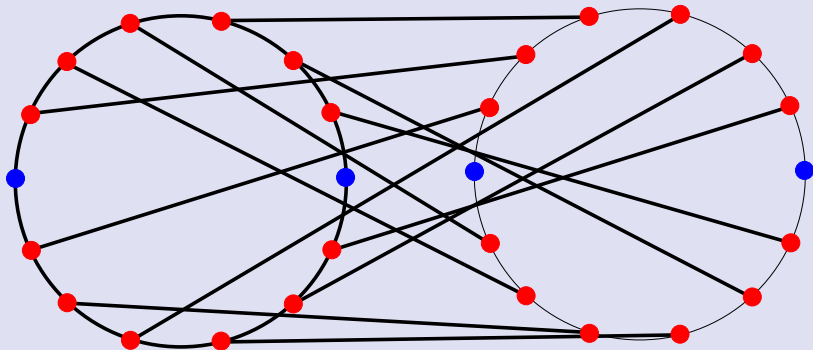
The Reduction (Metric TSP)

Sub-tour visiting all contact vertices of one cycle



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Final remarks:

- For equations with 3 variables, we construct a more efficient gadget (not shown)

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- Similar ideas can be used for Asymmetric TSP

Asymmetric TSP

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Input: An **asymmetric** metric space (V, d) (arc weighted digraph)

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Objective: Find a tour in (V, d) with minimum length

Theorem (Papadimitriou & Vempala (STOC'00))

It is NP-hard to approximate the Asymmetric TSP to within any factor less than $117/116$.

By using our bi-wheel amplifier methods, we obtain:

Asymmetric TSP

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Theorem (Karpinski, Lampis & S.'13)

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First improvement after more than a decade!

TSP with Distances 1 and 2

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Definition (TSP with distances 1 and 2 ((1,2)-TSP))

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Objective:

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$$d(v_i, v_j) = 1 \text{ if } \{v_i, v_j\} \in E \text{ and } 2 \text{ otherwise}$$

TSP with Distances 1 and 2

Theorem (Engebretsen & Karpinski (ICALP'01))

It is NP-hard to approximate the (1,2)-TSP to within any factor less than $741/740$.

By using wheel amplifier graphs combined with "parity gadgets", we obtain:

TSP with Distances 1 and 2

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By using wheel amplifier graphs combined with "parity gadgets", we obtain:

Theorem (Karpinski & S.'12)

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Graphic TSP

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Input: A graph $G = (V, E)$

Objective:

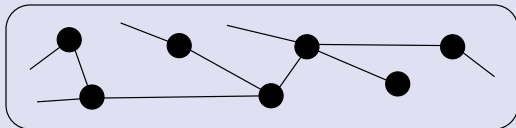
Definition (Graphic TSP)

Input: A graph $G = (V, E)$

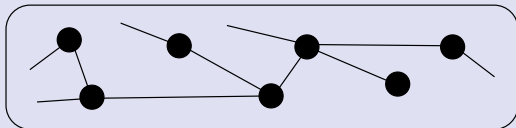
Objective: Find a tour with minimum length

$d(v_i, v_j)$ is defined by the shortest-path distance of v_i and v_j in G

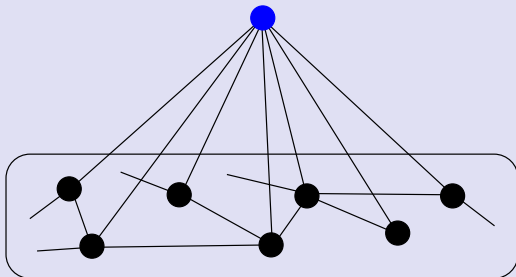
Reducing (1,2)-TSP to Graphic TSP



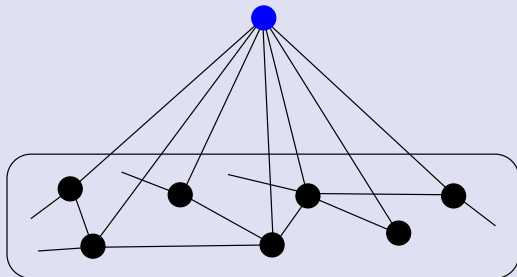
Reducing (1,2)-TSP to Graphic TSP



Reducing (1,2)-TSP to Graphic TSP



Reducing (1,2)-TSP to Graphic TSP



Implying the best up to now inapproximability factor for Graphic TSP

Subcubic & Cubic Instances

Comparison of inapproximability results

Problem	Previously best known	Our Result
(1,2)-TSP on cubic graphs	1291/1290 [CKK02]	
(1,2)-TSP on subcubic graphs	787/786 [CKK02]	
Graphic TSP on cubic graphs	–	
Graphic TSP on subcubic graphs	–	

Subcubic & Cubic Instances

Comparison of inapproximability results

Problem	Previously best known	Our Result
(1,2)-TSP on cubic graphs	1291/1290 [CKK02]	1141/1140
(1,2)-TSP on subcubic graphs	787/786 [CKK02]	
Graphic TSP on cubic graphs	–	
Graphic TSP on subcubic graphs	–	

Subcubic & Cubic Instances

Comparison of inapproximability results

Problem	Previously best known	Our Result
(1,2)-TSP on cubic graphs	1291/1290 [CKK02]	1141/1140
(1,2)-TSP on subcubic graphs	787/786 [CKK02]	673/672
Graphic TSP on cubic graphs	–	
Graphic TSP on subcubic graphs	–	

Subcubic & Cubic Instances

Comparison of inapproximability results

Problem	Previously best known	Our Result
(1,2)-TSP on cubic graphs	1291/1290 [CKK02]	1141/1140
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Graphic TSP on cubic graphs	–	1153/1152
Graphic TSP on subcubic graphs	–	

First inapproximability results at all!

Subcubic & Cubic Instances

Comparison of inapproximability results

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(1,2)-TSP on cubic graphs	1291/1290 [CKK02]	1141/1140
(1,2)-TSP on subcubic graphs	787/786 [CKK02]	673/672
Graphic TSP on cubic graphs	–	1153/1152
Graphic TSP on subcubic graphs	–	685/684

First inapproximability results at all!

Further Results

Further related results on approximability of the problems of:

- Shortest Superstring

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- Steiner Tree with distances 1 and 2
- Metric Dimension
- Hypergraph Vertex Cover

Conclusions:

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- Improving the inapproximability bounds for the TSP and the Steiner Tree problem?
- Better amplifier constructions?
- New global PCP-system constructions for TSP?

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On upper bounds side:

- Improving general upper approximation bound for metric TSP below $3/2$ (1.50)?



Further research:

On upper bounds side:

- Improving general upper approximation bound for metric TSP below $3/2$ (1.50)?
- Improving upper approximation bound for cubic Graphic TSP below $4/3$ (1.33)?



Thank You!