

*Baby steps towards TSP  
inapproximability*

Michael Lampis  
KTH Royal Institute of Technology

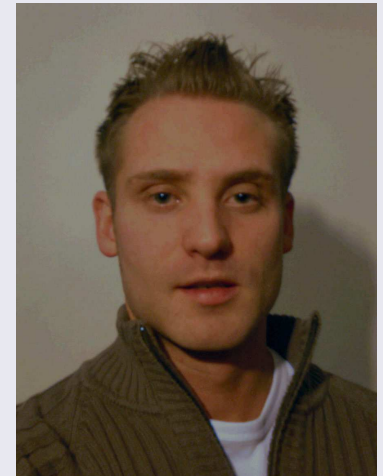


May 3, 2013

# Acknowledgements

The material in this talk is based on the following papers:

- “Improved Inapproximability for TSP”, APPROX’12
- “New Inapproximability Bounds for TSP”, arxiv’13 (joint work with Marek Karpinski and Richard Schmied)



# The Story

- The Traveling Salesman problem is famous and important. Unfortunately, it's NP-hard.
  - How well can we approximate it?
  - Big breakthroughs in algorithms recently. We set out to improve on **inapproximability** results.

# The Story

- The Traveling Salesman problem is famous and important. Unfortunately, it's NP-hard.
  - How well can we approximate it?
  - Big breakthroughs in algorithms recently. We set out to improve on **inapproximability** results.

## Main idea

- Hardness obtained through a reduction from a Constraint Satisfaction Problem (CSP)



# The Story

- The Traveling Salesman problem is famous and important. Unfortunately, it's NP-hard.
  - How well can we approximate it?
  - Big breakthroughs in algorithms recently. We set out to improve on **inapproximability** results.

## Main idea

- Reduction is easier if CSP has bounded # of occurrences



# The Story

- The Traveling Salesman problem is famous and important. Unfortunately, it's NP-hard.
  - How well can we approximate it?
  - Big breakthroughs in algorithms recently. We set out to improve on **inapproximability** results.

## Main idea

- We need inapproximability results for CSPs with bounded # of occurrences



# The Story

- The Traveling Salesman problem is famous and important. Unfortunately, it's NP-hard.
  - How well can we approximate it?
  - Big breakthroughs in algorithms recently. We set out to improve on **inapproximability** results.

## Main idea

- Such results use expander graphs



# The Story

- The Traveling Salesman problem is famous and important. Unfortunately, it's NP-hard.
  - How well can we approximate it?
  - Big breakthroughs in algorithms recently. We set out to improve on **inapproximability** results.

## Main idea

- Expander graphs →
  - Hardness for bounded occurrence CSPs →
  - Hardness for TSP





# The Actual Story

## Better Expanders



## Better Expanders

- A local improvement argument gives (slightly) better expander graphs than those already in the literature.

# The Actual Story

## Better Expanders

- A local improvement argument gives (slightly) better expander graphs than those already in the literature.



See “Local Improvement Gives Better Expanders”, arxiv’12

# The Actual Story

## Better Expanders

- A local improvement argument gives (slightly) better expander graphs than those already in the literature.



See “Local Improvement Gives Better Expanders”, arxiv’12

- But improvement is too small to matter!



# The Actual Story

Second attempt:

- We will rely on amplifier graph constructions due to Berman and Karpinski.

# The Actual Story

## Second attempt:

- We will rely on amplifier graph constructions due to Berman and Karpinski.
- These will help us construct inapproximable CSPs with 3 or 5 occurrences for each variable.

# The Actual Story

## Second attempt:

- We will rely on amplifier graph constructions due to Berman and Karpinski.
- These will help us construct inapproximable CSPs with 3 or 5 occurrences for each variable.
- We will reduce these to TSP (and ATSP).

# The Actual Story

## Second attempt:

- We will rely on amplifier graph constructions due to Berman and Karpinski.
- These will help us construct inapproximable CSPs with 3 or 5 occurrences for each variable.
- We will reduce these to TSP (and ATSP).
- End result: **simpler** construction and **better** inapproximability constants!





# The Actual Story

## Second attempt:

- We will rely on amplifier graph constructions due to Berman and Karpinski.
- These will help us construct inapproximable CSPs with 3 or 5 occurrences for each variable.
- We will reduce these to TSP (and ATSP).
- End result: **simpler** construction and **better** inapproximability constants!
- Warning: don't expect a **big** improvement.



# The Traveling Salesman Problem

# The Traveling Salesman Problem

Input:

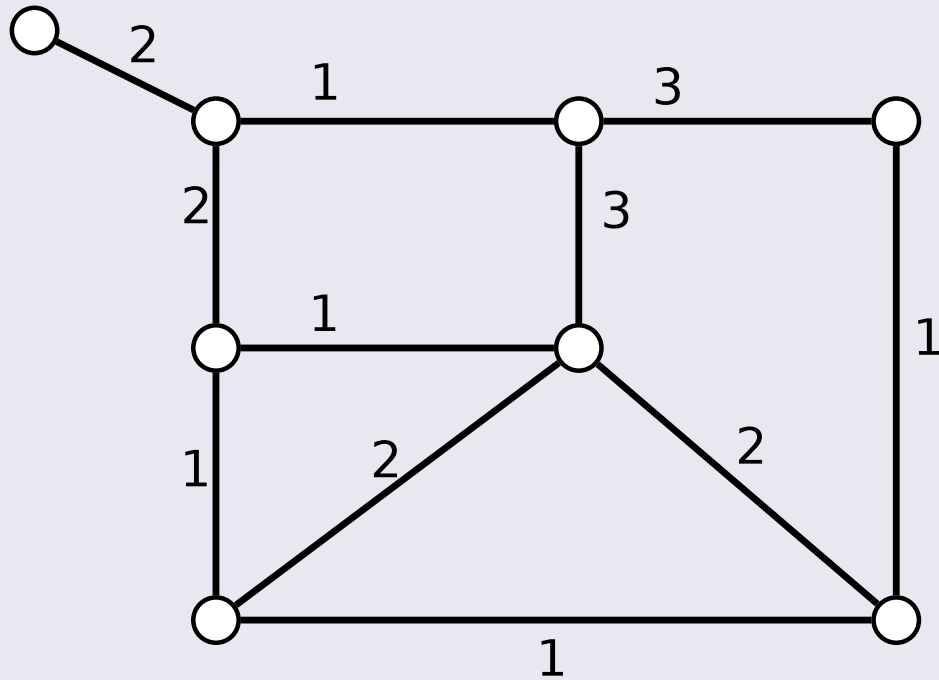
- An edge-weighted graph  $G(V, E)$

Objective:

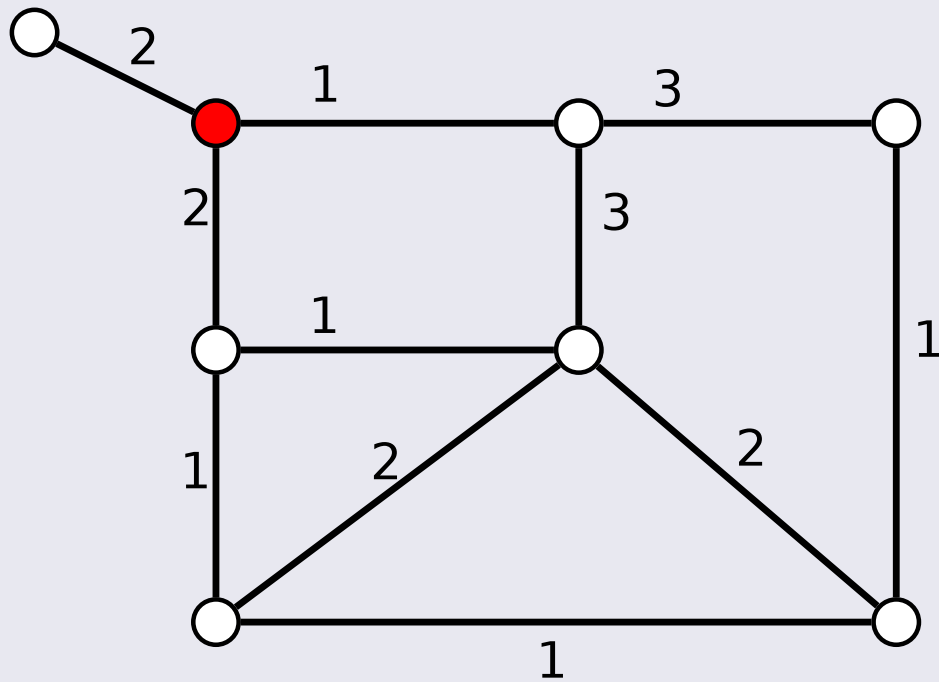
- Find an ordering of the vertices  $v_1, v_2, \dots, v_n$  such that  $d(v_1, v_2) + d(v_2, v_3) + \dots + d(v_n, v_1)$  is minimized.
- $d(v_i, v_j)$  is the shortest-path distance of  $v_i, v_j$  on  $G$



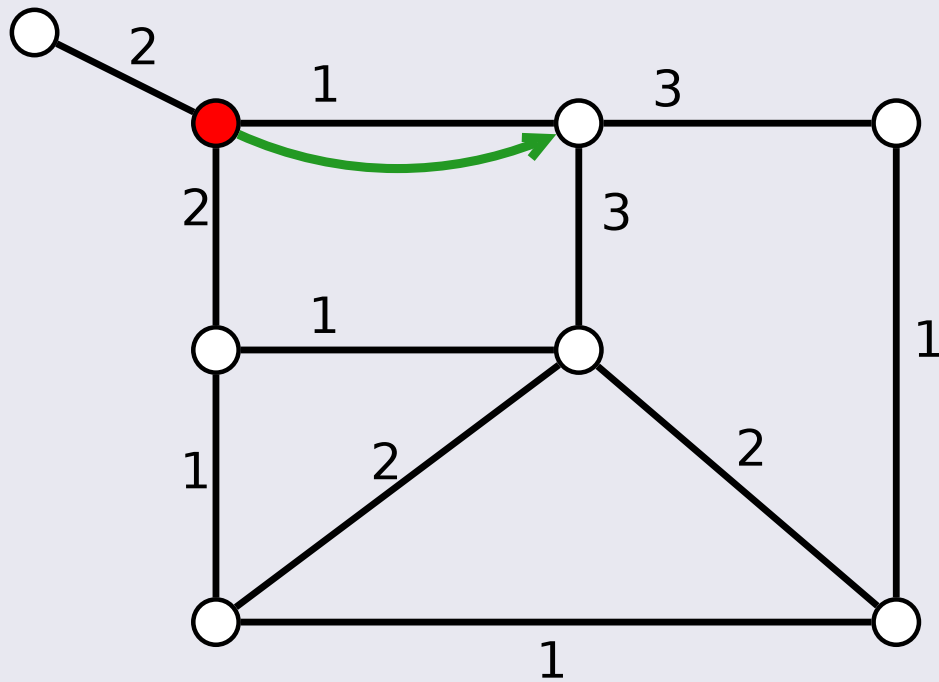
# The Traveling Salesman Problem



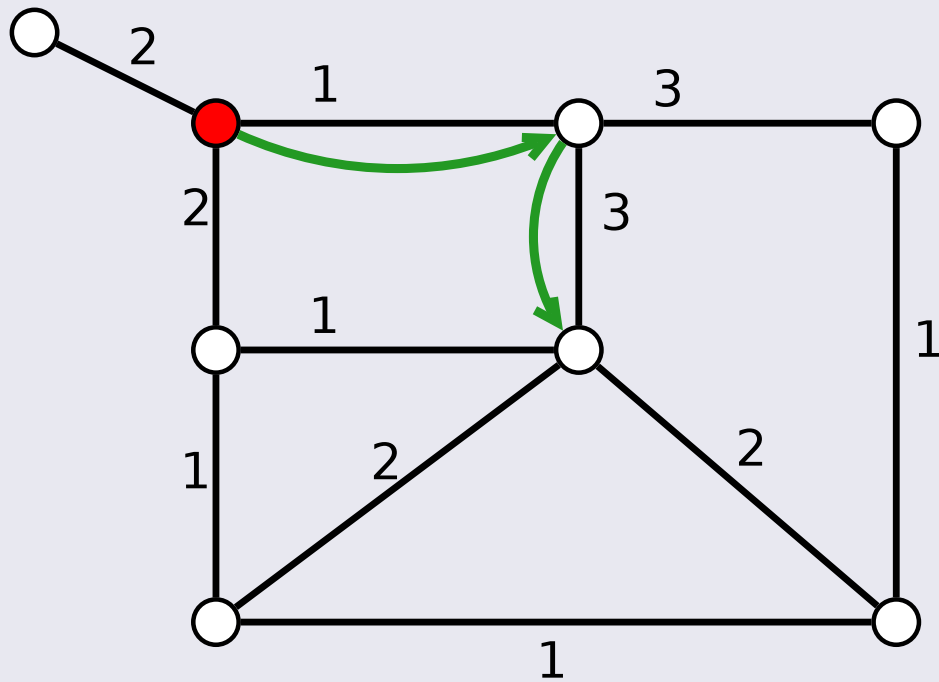
# The Traveling Salesman Problem



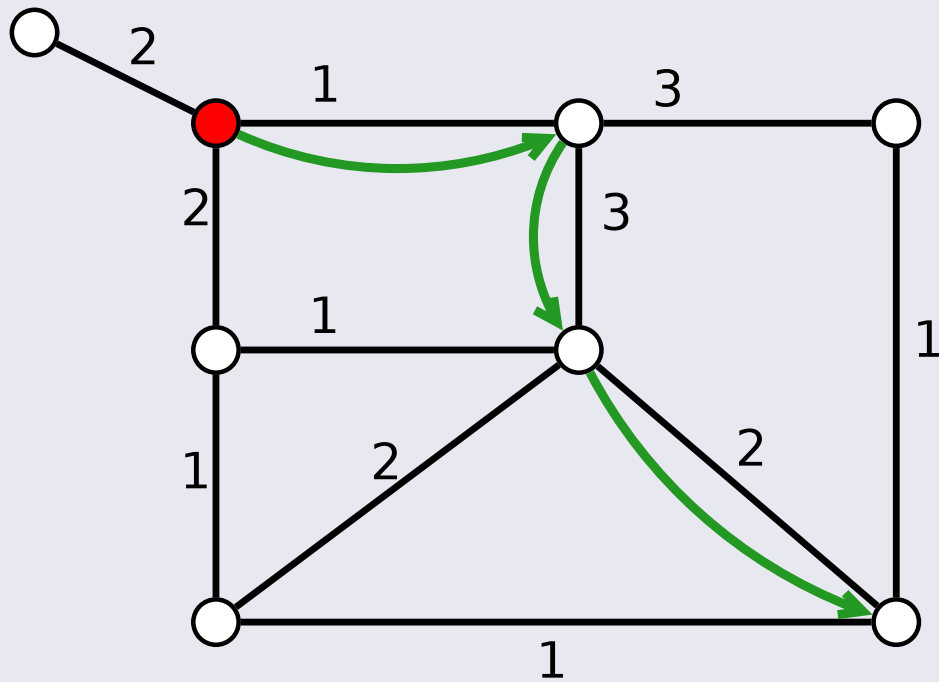
# The Traveling Salesman Problem



# The Traveling Salesman Problem

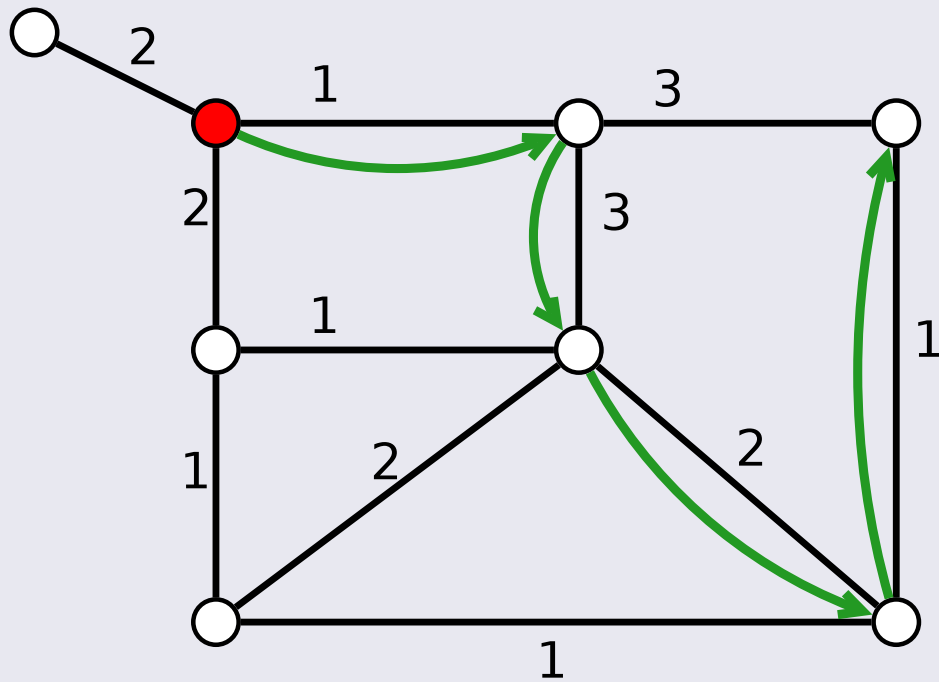


# The Traveling Salesman Problem

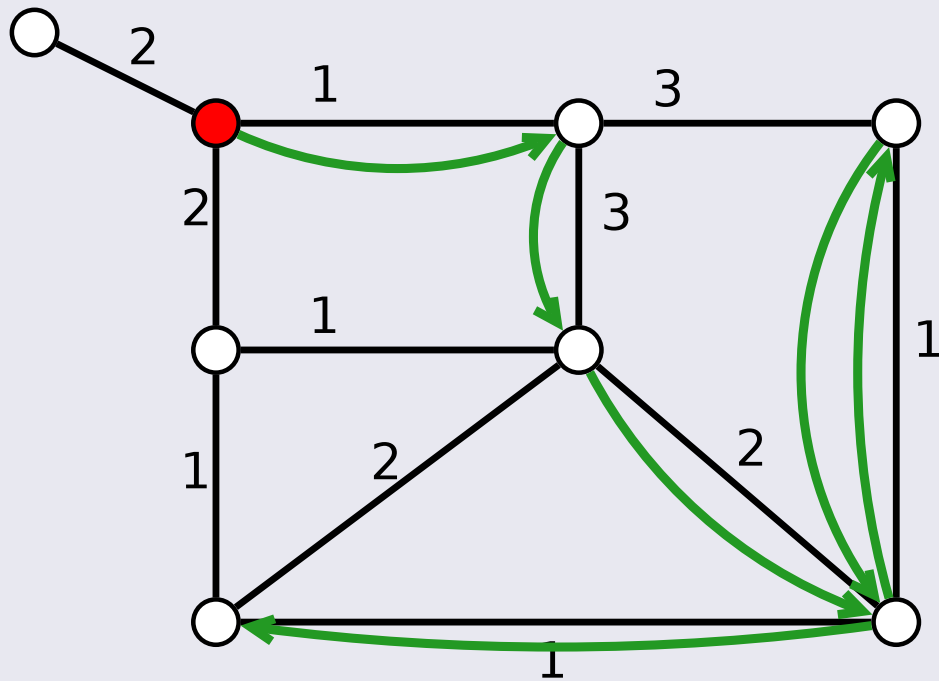




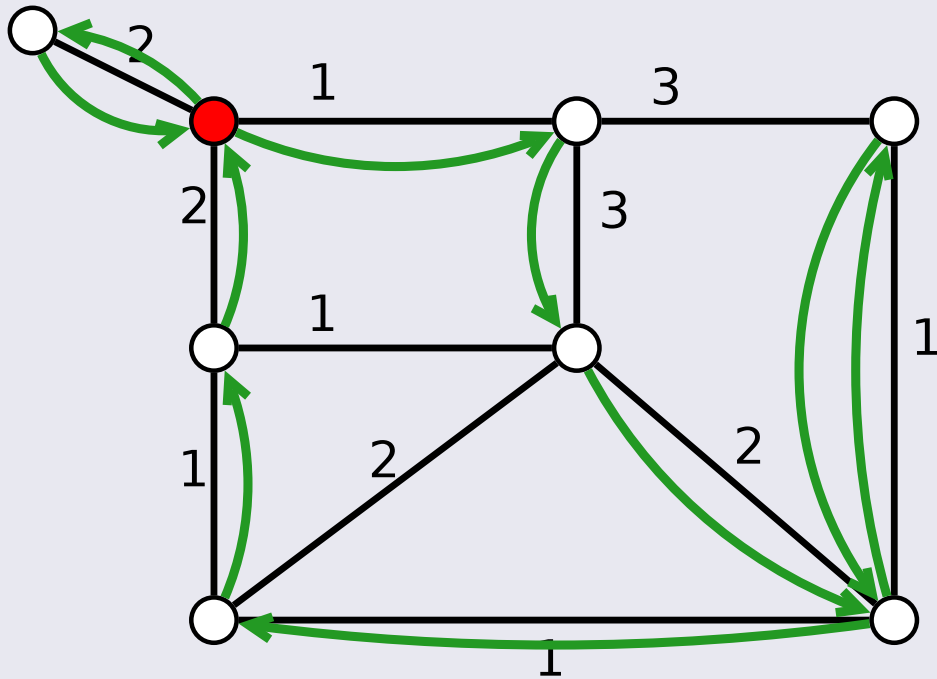
# The Traveling Salesman Problem



# The Traveling Salesman Problem




# The Traveling Salesman Problem



# TSP Approximations – Upper bounds


- $\frac{3}{2}$  approximation (Christofides 1976)

For graphic (un-weighted) case

- $\frac{3}{2} - \epsilon$  approximation (Oveis Gharan et al. FOCS '11)
- 1.461 approximation (Mömke and Svensson FOCS '11) 
- $\frac{13}{9}$  approximation (Mucha STACS '12)
- 1.4 approximation (Sebö and Vygen arXiv '12)
- For ATSP the best ratio is  $O(\log n / \log \log n)$  (Asadpour et al. SODA '10)




# TSP Approximations – Lower bounds

- Problem is APX-hard (Papadimitriou and Yannakakis '93)
- $\frac{5381}{5380}$ -inapproximable, ATSP  $\frac{2805}{2804}$  (Engebretsen STACS '99) 
- $\frac{3813}{3812}$ -inapproximable (Böckenhauer et al. STACS '00)
- $\frac{220}{219}$ -inapproximable, ATSP  $\frac{117}{116}$  (Papadimitriou and Vempala STOC '00, Combinatorica '06)



# TSP Approximations – Lower bounds

- Problem is APX-hard (Papadimitriou and Yannakakis '93)
- $\frac{5381}{5380}$ -inapproximable, ATSP  $\frac{2805}{2804}$  (Engebretsen STACS '99) 
- $\frac{3813}{3812}$ -inapproximable (Böckenhauer et al. STACS '00)
- $\frac{220}{219}$ -inapproximable, ATSP  $\frac{117}{116}$  (Papadimitriou and Vempala STOC '00, Combinatorica '06)



This talk:

## Theorem

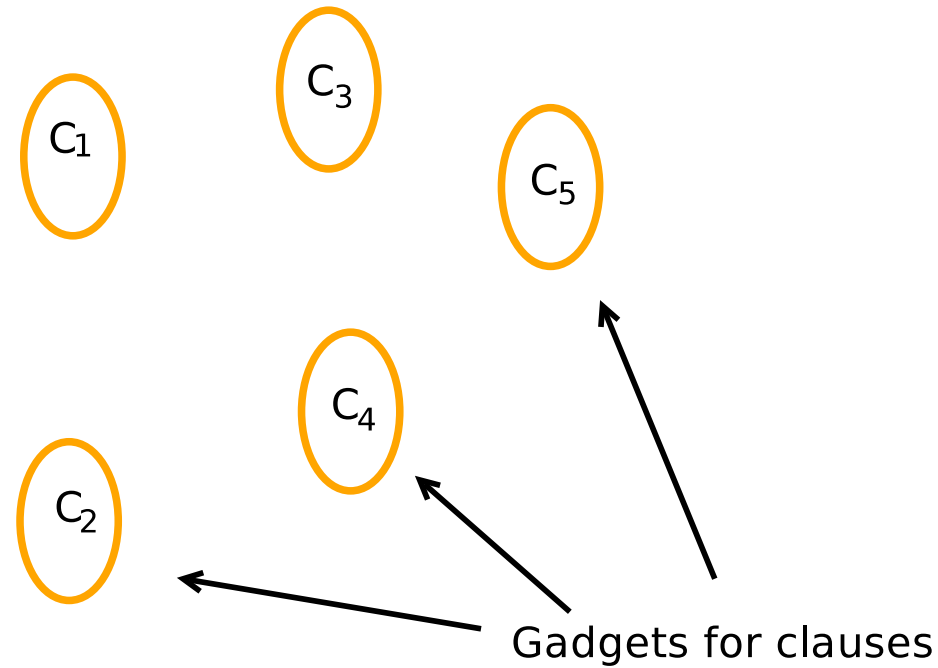
It is NP-hard to approximate TSP better than  $\frac{123}{122}$  and ATSP better than  $\frac{75}{74}$ .

# Reduction Technique



We reduce some inapproximable CSP (e.g. MAX-3SAT) to TSP.

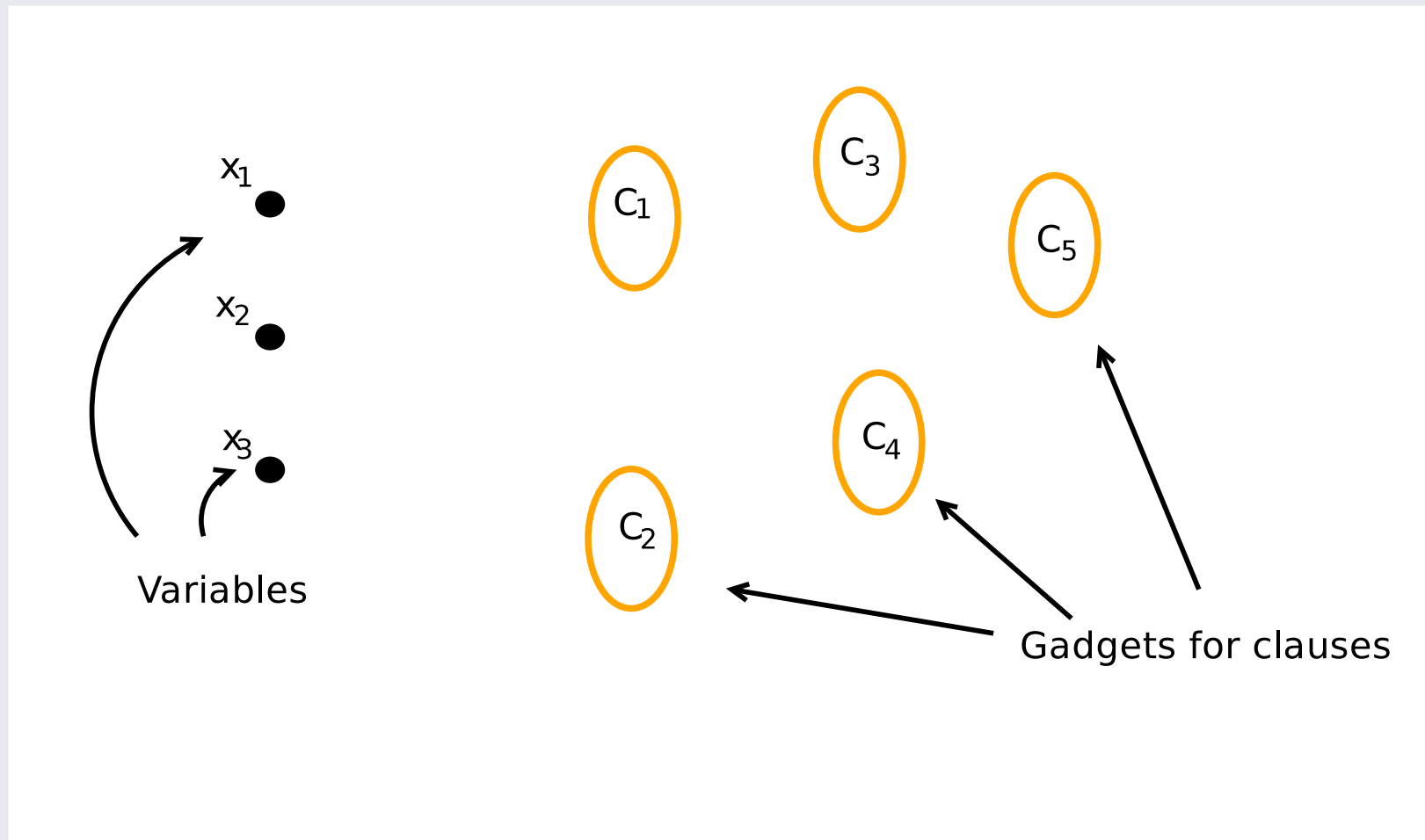
# Reduction Technique



First, design some gadgets to represent the clauses

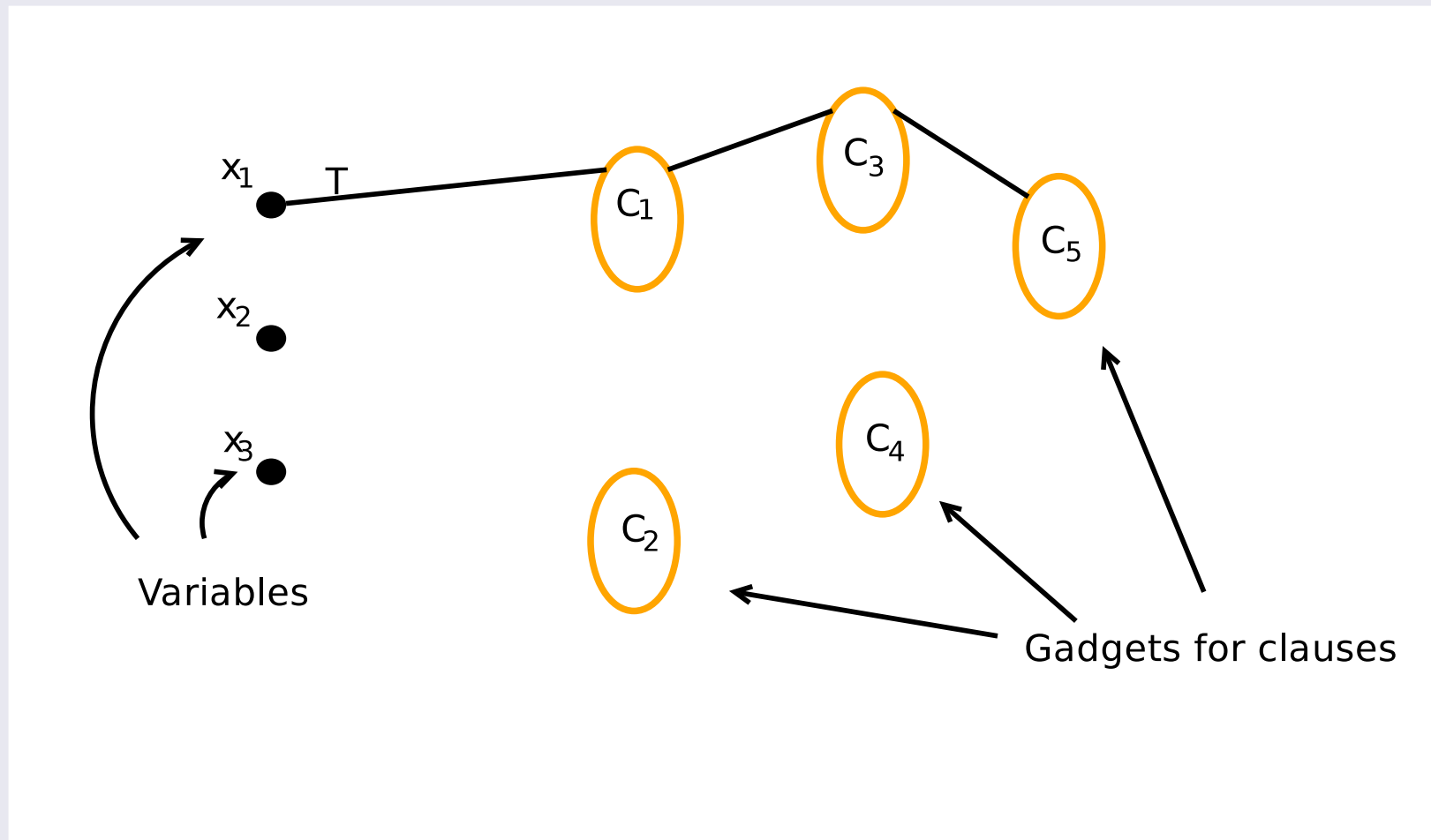


# Reduction Technique



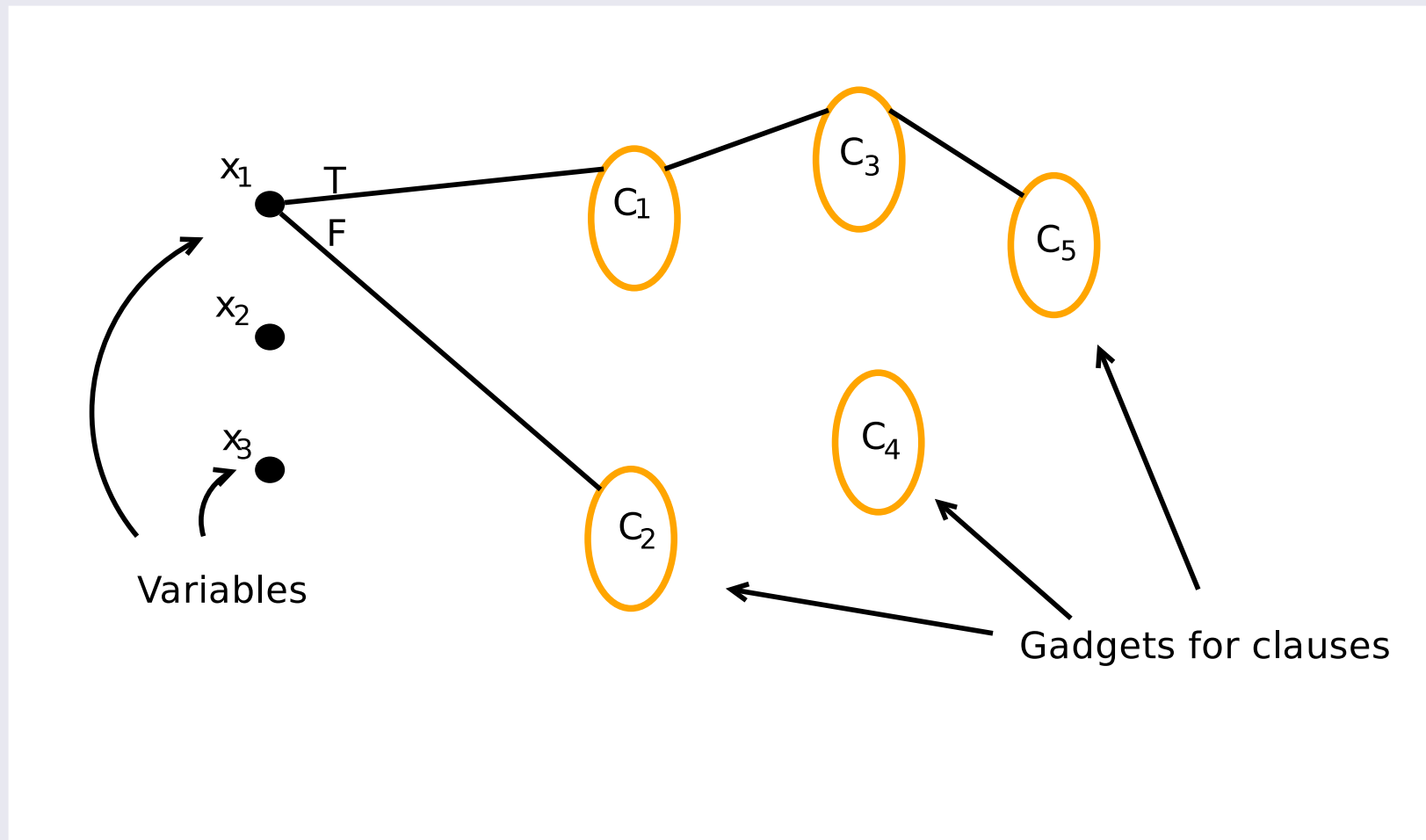
Then, add some choice vertices to represent truth assignments to variables

# Reduction Technique



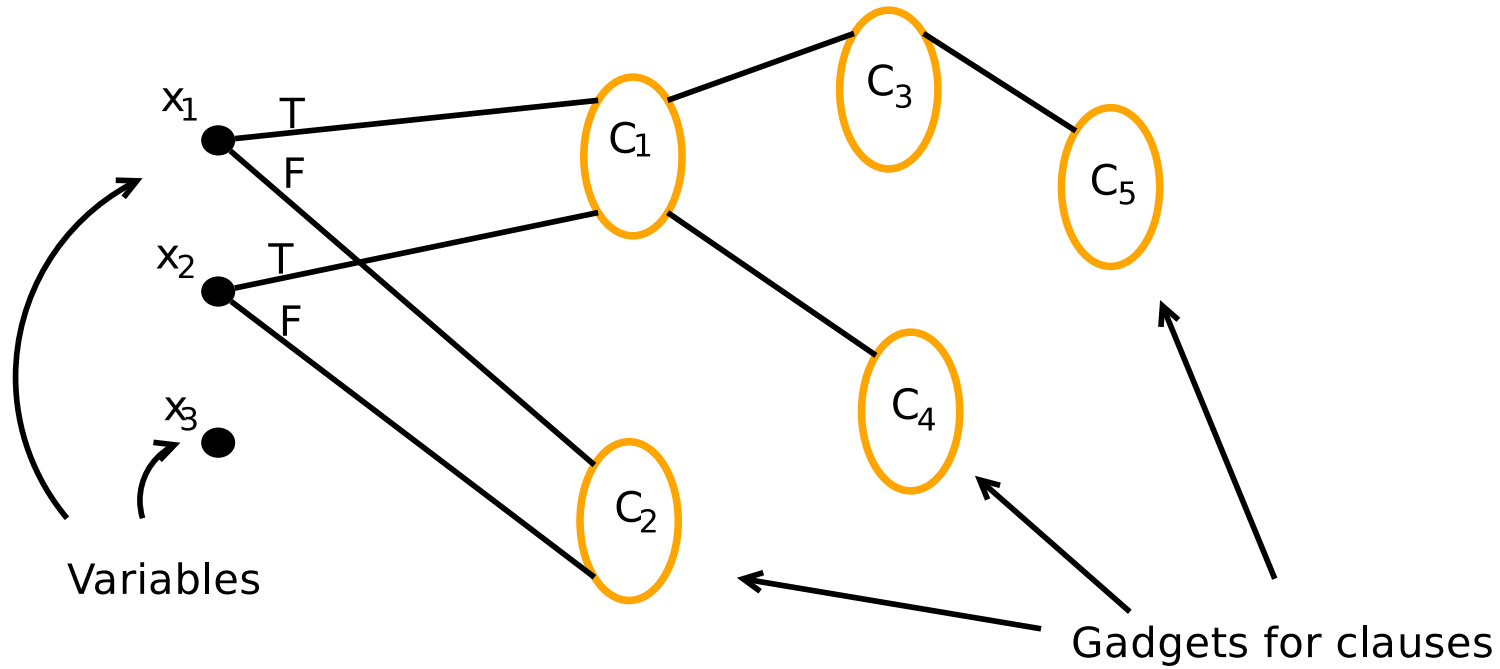
For each variable, create a path through clauses where it appears positive

# Reduction Technique

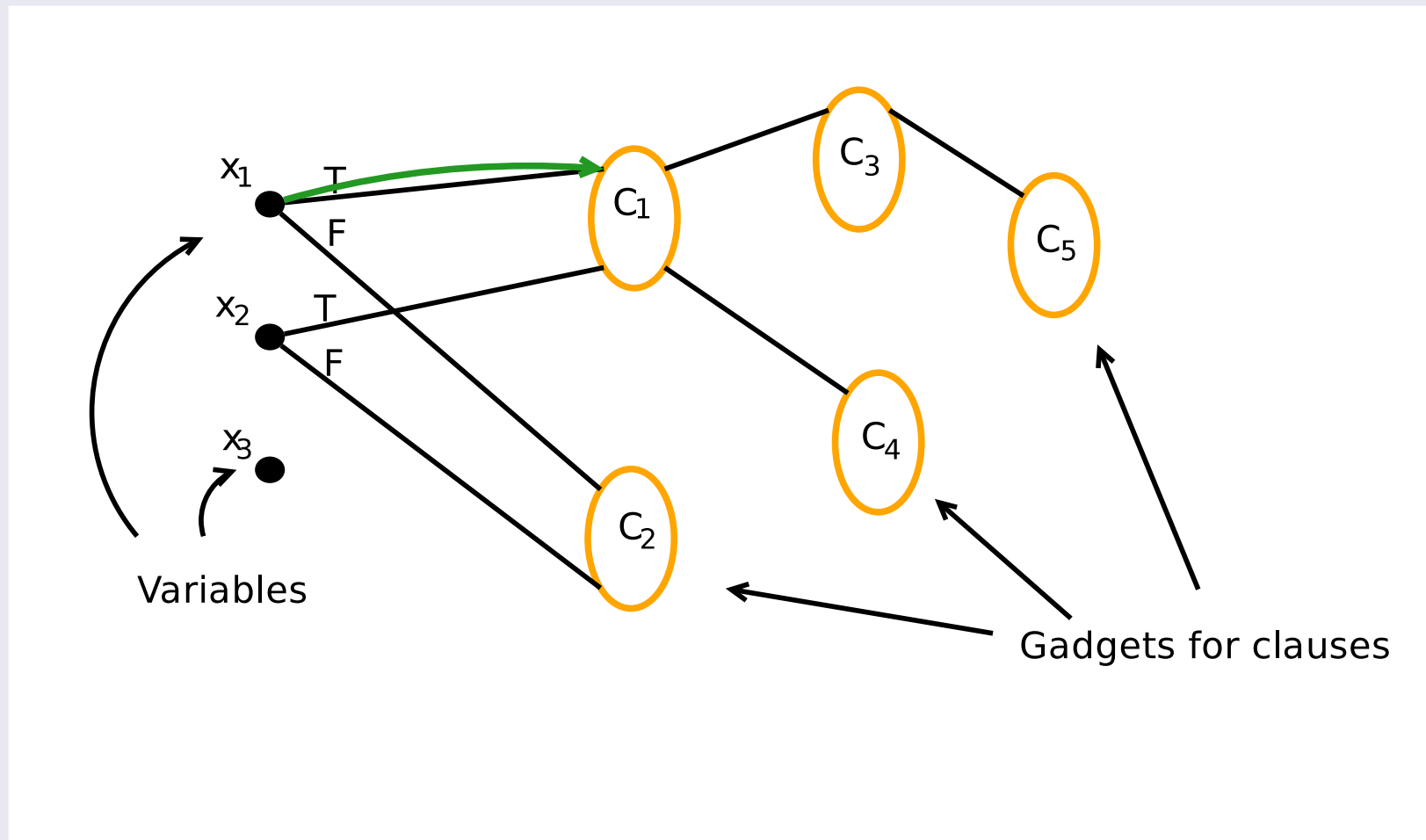


... and another path for its negative appearances

# Reduction Technique

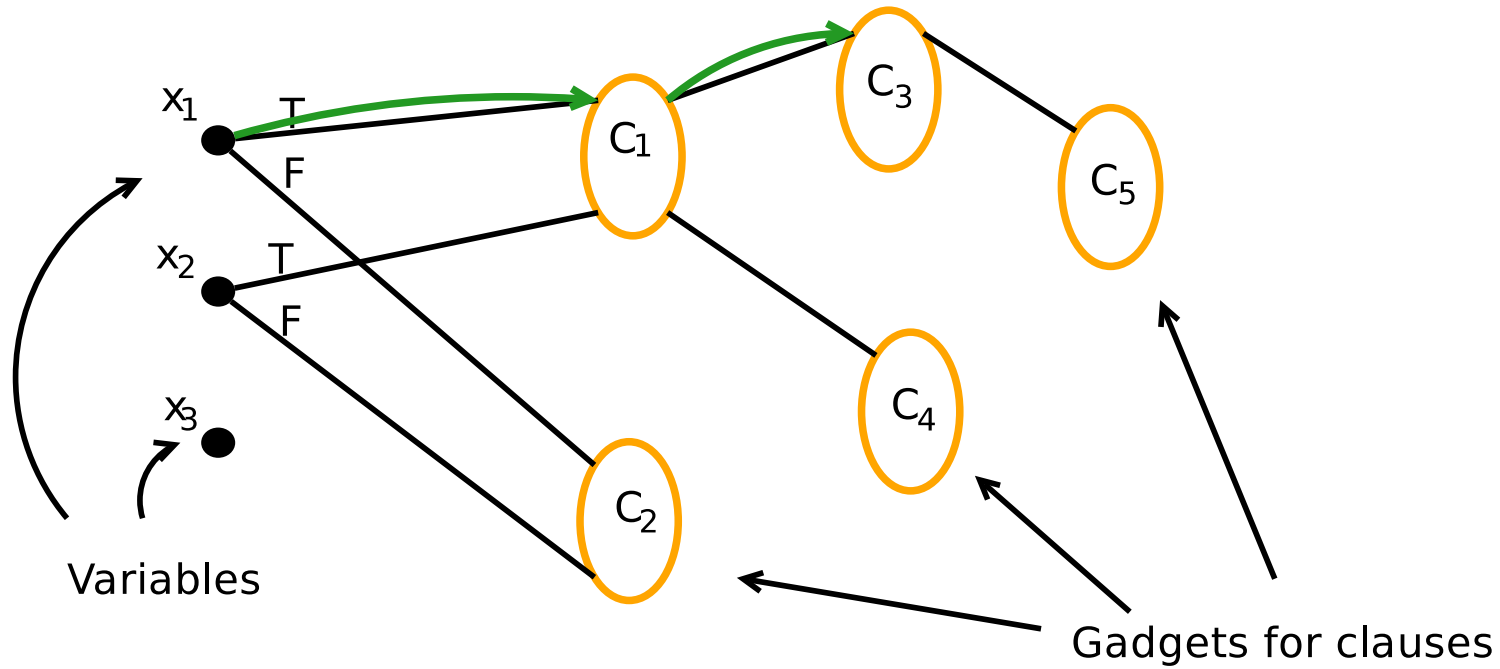


# Reduction Technique

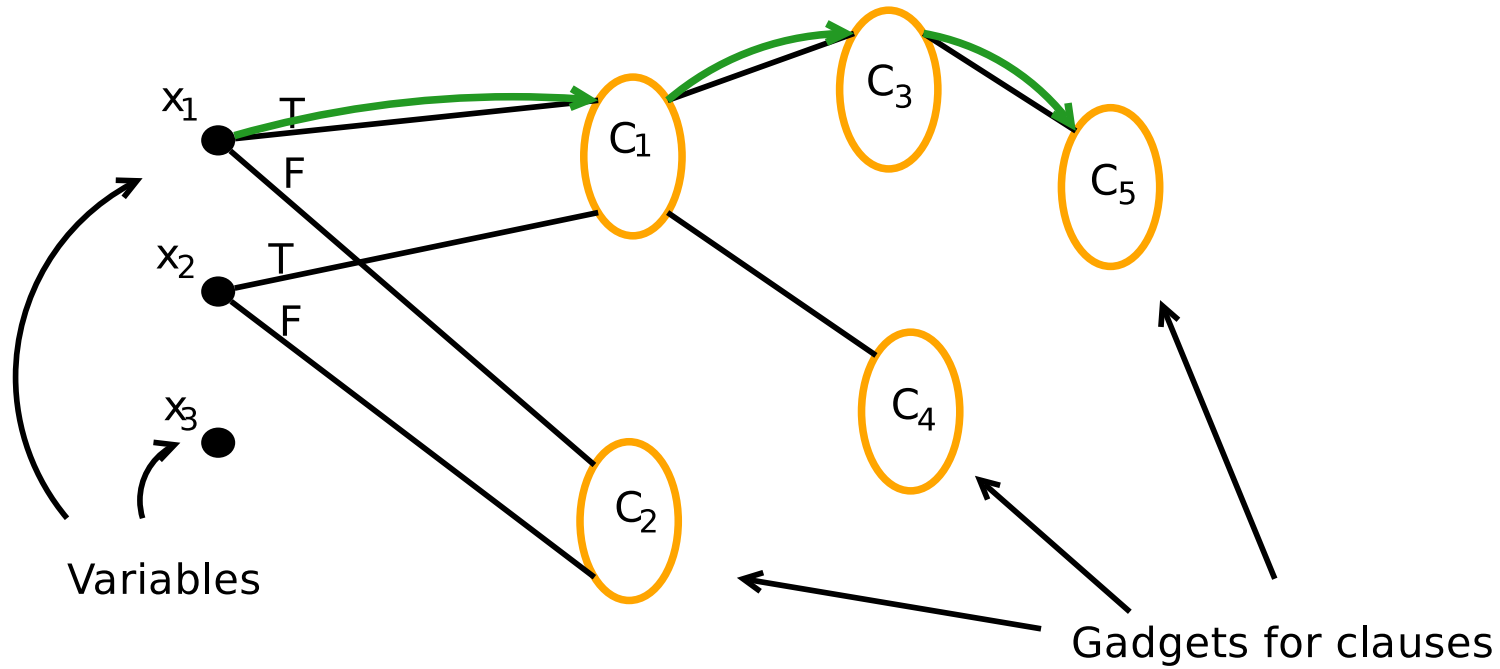


A truth assignment dictates a general path

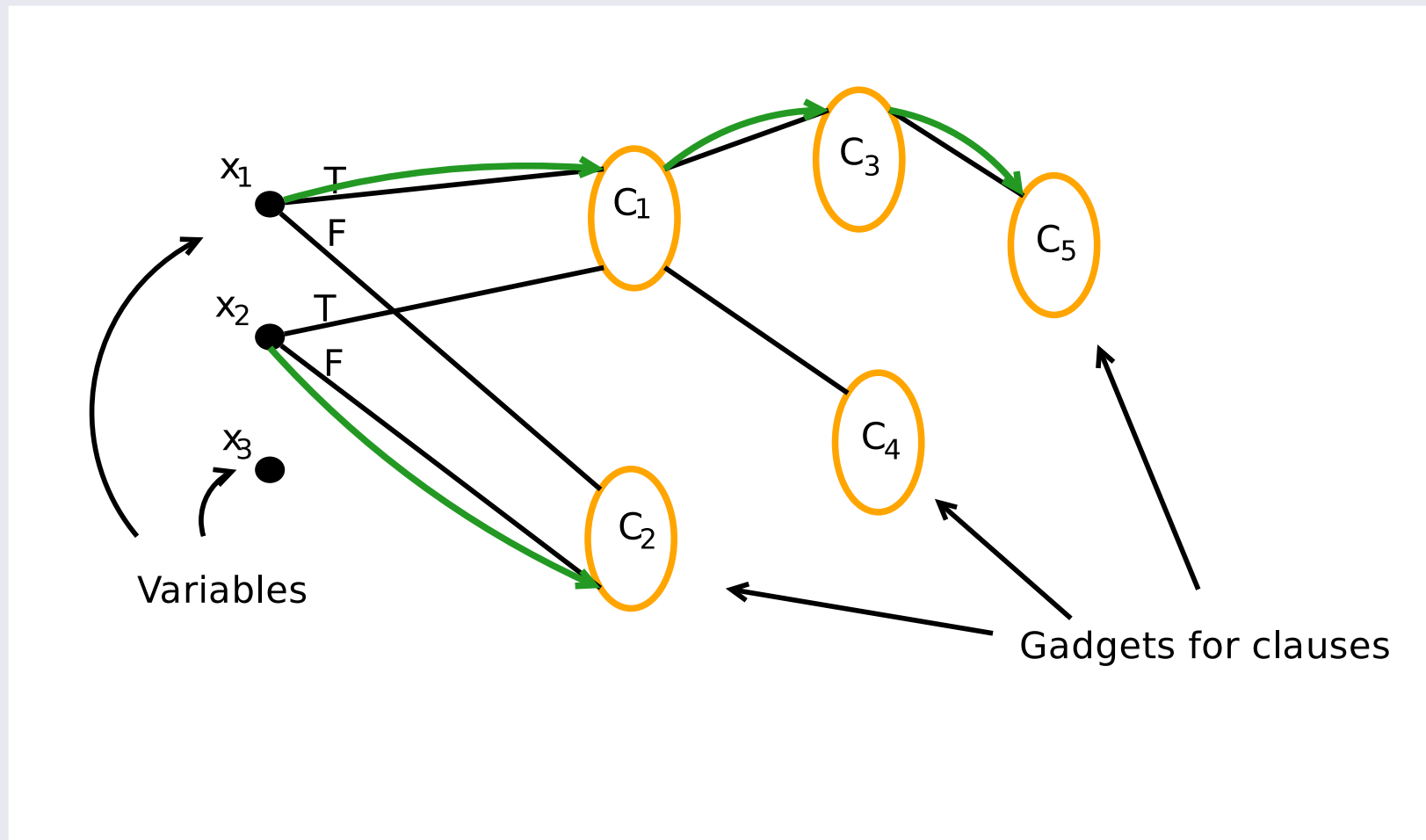
# Reduction Technique



# Reduction Technique



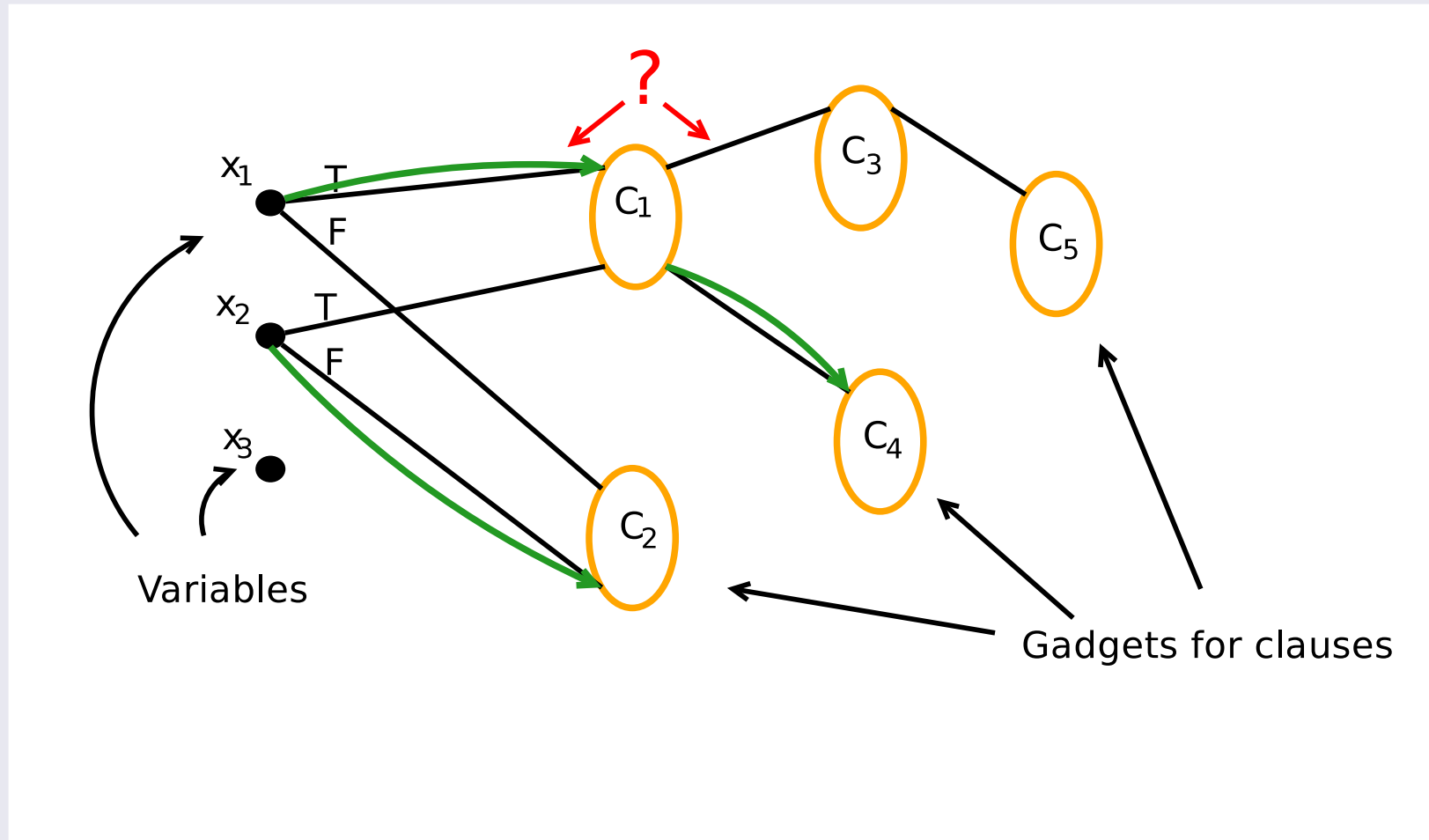
# Reduction Technique



We must make sure that gadgets are cheaper to traverse if corresponding clause is satisfied



# Reduction Technique



For the converse direction we must make sure that "cheating" tours are not optimal!

# How to ensure consistency

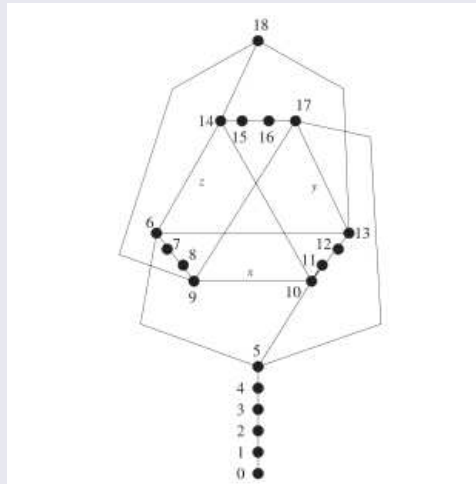


Figure 6. Equation gadget for the symmetric TSP

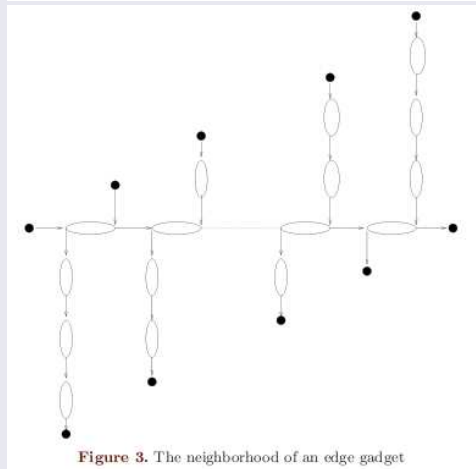


Figure 3. The neighborhood of an edge gadget

- Papadimitriou and Vempala design a gadget for Parity.
- They eliminate variable vertices altogether.
- Consistency is achieved by hooking up gadgets "randomly"
- In fact gadgets that share a variable are connected according to the structure dictated by a special graph
- The graph is called a "pusher". Its existence is proved using the probabilistic method.

# How to ensure consistency

- Basic idea here: consistency would be easy if each variable occurred at most  $c$  times,  $c$  a constant.
  - Cheating would only help a tour "fix" a bounded number of clauses.

# How to ensure consistency

- Basic idea here: consistency would be easy if each variable occurred at most  $c$  times,  $c$  a constant.
  - Cheating would only help a tour "fix" a bounded number of clauses.
- We will rely on techniques and tools used to prove inapproximability for bounded-occurrence CSPs.
  - This is where expander graphs are important.
  - Main tool: "amplifier graph" constructions due to Berman and Karpinski.

# How to ensure consistency

- Basic idea here: consistency would be easy if each variable occurred at most  $c$  times,  $c$  a constant.
  - Cheating would only help a tour "fix" a bounded number of clauses.
- We will rely on techniques and tools used to prove inapproximability for bounded-occurrence CSPs.
  - This is where expander graphs are important.
  - Main tool: "amplifier graph" constructions due to Berman and Karpinski.
- Result: an easier hardness proof that can be broken down into independent pieces, and also gives improved bounds.

# Expander and Amplifier Graphs

# Expander Graphs

- Informal description:

An expander graph is a **well-connected** and **sparse** graph.

# Expander Graphs

- Informal description:

An expander graph is a **well-connected** and **sparse** graph.

- Definition:

A graph  $G(V, E)$  is an expander if

- For all  $S \subseteq V$  with  $|S| \leq \frac{|V|}{2}$  we have for some constant  $c$

$$\frac{|E(S, V \setminus S)|}{|S|} \geq c$$

- The maximum degree  $\Delta$  is bounded



# Expander Graphs

- Informal description:

An expander graph is a **well-connected** and **sparse** graph.

- In any possible partition of the vertices into two sets, there are **many** edges crossing the cut.
- This is achieved even though the graph has low degree, therefore few edges.

# Expander Graphs

- Informal description:

An expander graph is a **well-connected** and **sparse** graph.

- In any possible partition of the vertices into two sets, there are **many** edges crossing the cut.
- This is achieved even though the graph has low degree, therefore few edges.

Example:

# Expander Graphs

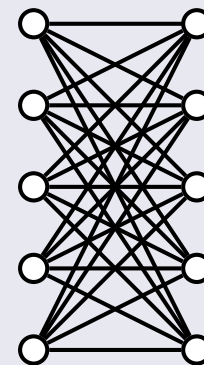
- Informal description:

An expander graph is a **well-connected** and **sparse** graph.

- In any possible partition of the vertices into two sets, there are **many** edges crossing the cut.
- This is achieved even though the graph has low degree, therefore few edges.

Example:

A complete bipartite graph is well-connected but **not** sparse.



# Expander Graphs

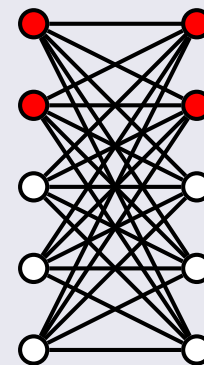
- Informal description:

An expander graph is a **well-connected** and **sparse** graph.

- In any possible partition of the vertices into two sets, there are **many** edges crossing the cut.
- This is achieved even though the graph has low degree, therefore few edges.

Example:

A complete bipartite graph is well-connected but **not** sparse.



# Expander Graphs

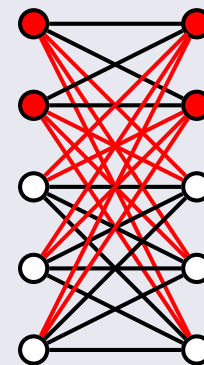
- Informal description:

An expander graph is a **well-connected** and **sparse** graph.

- In any possible partition of the vertices into two sets, there are **many** edges crossing the cut.
- This is achieved even though the graph has low degree, therefore few edges.

Example:

A complete bipartite graph is well-connected but **not** sparse.



# Expander Graphs

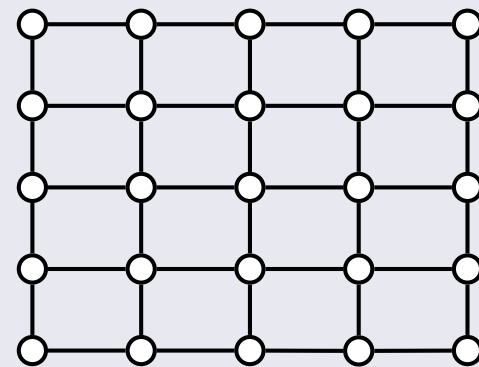
- Informal description:

An expander graph is a **well-connected** and **sparse** graph.

- In any possible partition of the vertices into two sets, there are **many** edges crossing the cut.
- This is achieved even though the graph has low degree, therefore few edges.

Example:

A grid is sparse but **not** well-connected.



# Expander Graphs

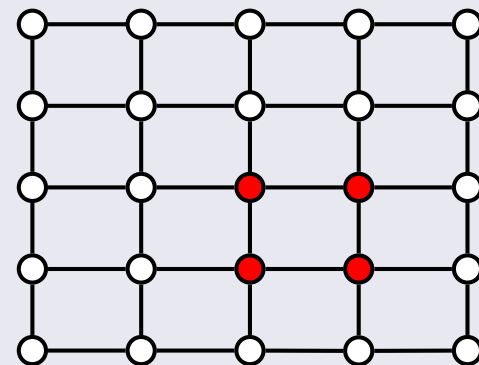
- Informal description:

An expander graph is a **well-connected** and **sparse** graph.

- In any possible partition of the vertices into two sets, there are **many** edges crossing the cut.
- This is achieved even though the graph has low degree, therefore few edges.

Example:

A grid is sparse but **not** well-connected.



# Expander Graphs

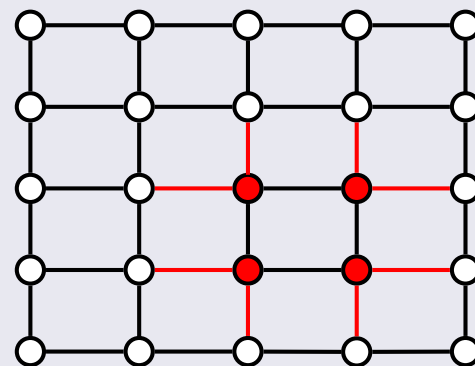
- Informal description:

An expander graph is a **well-connected** and **sparse** graph.

- In any possible partition of the vertices into two sets, there are **many** edges crossing the cut.
- This is achieved even though the graph has low degree, therefore few edges.

Example:

A grid is sparse but **not** well-connected.





# Expander Graphs

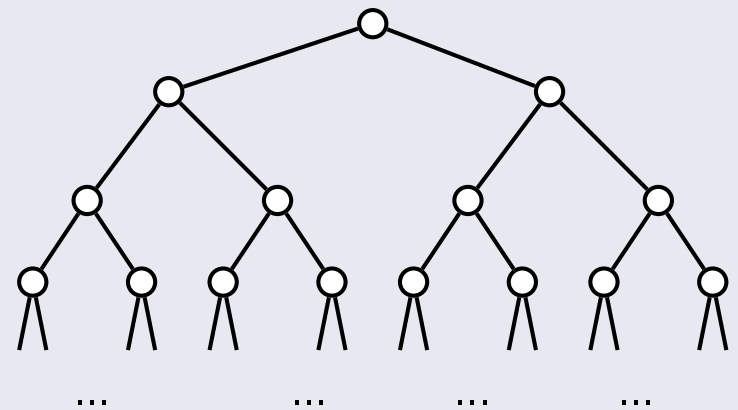
- Informal description:

An expander graph is a **well-connected** and **sparse** graph.

- In any possible partition of the vertices into two sets, there are **many** edges crossing the cut.
- This is achieved even though the graph has low degree, therefore few edges.

Example:

An **infinite** binary tree is a good expander.



# Expander Graphs

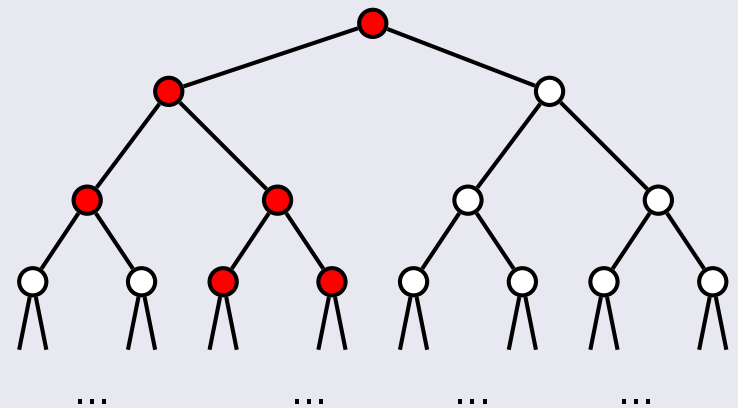
- Informal description:

An expander graph is a **well-connected** and **sparse** graph.

- In any possible partition of the vertices into two sets, there are **many** edges crossing the cut.
- This is achieved even though the graph has low degree, therefore few edges.

Example:

An **infinite** binary tree is a good expander.



# Expander Graphs

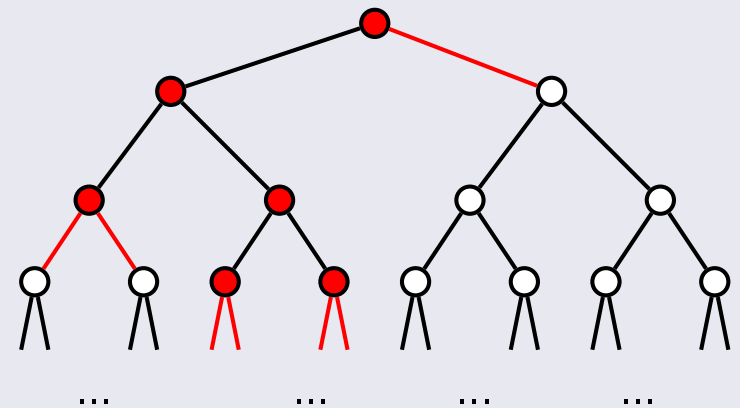
- Informal description:

An expander graph is a **well-connected** and **sparse** graph.

- In any possible partition of the vertices into two sets, there are **many** edges crossing the cut.
- This is achieved even though the graph has low degree, therefore few edges.

Example:

An **infinite** binary tree is a good expander.



# Applications of Expanders

Expander graphs have a number of applications

- Proof of PCP theorem
- Derandomization
- Error-correcting codes

# Applications of Expanders

Expander graphs have a number of applications

- Proof of PCP theorem
- Derandomization
- Error-correcting codes
- ... and inapproximability of bounded occurrence CSPs!

## Expanders and inapproximability

- Consider the standard reduction from 3-SAT to 3-OCC-3-SAT
  - Replace each appearance of variable  $x$  with a fresh variable  $x_1, x_2, \dots, x_n$
  - Add the clauses  $(x_1 \rightarrow x_2) \wedge (x_2 \rightarrow x_3) \wedge \dots \wedge (x_n \rightarrow x_1)$

## Expanders and inapproximability

- Consider the standard reduction from 3-SAT to 3-OCC-3-SAT
  - Replace each appearance of variable  $x$  with a fresh variable  $x_1, x_2, \dots, x_n$
  - Add the clauses  $(x_1 \rightarrow x_2) \wedge (x_2 \rightarrow x_3) \wedge \dots \wedge (x_n \rightarrow x_1)$

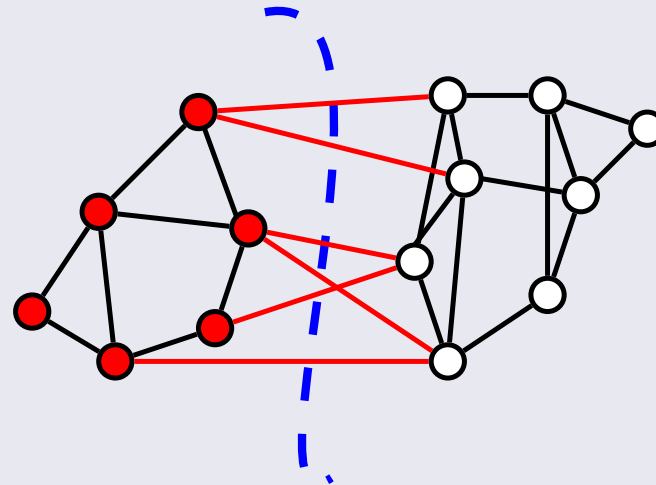
**Problem:** This does not preserve inapproximability!

- We could add  $(x_i \rightarrow x_j)$  for all  $i, j$ .
- This ensures consistency but adds too many clauses and does not decrease number of occurrences!

# Applications of Expanders

## Expanders and inapproximability

- We modify this using a 1-expander [Papadimitriou Yannakakis 91]
  - Recall: a 1-expander is a graph s.t. in each partition of the vertices the number of edges crossing the cut is larger than the number of vertices of the smaller part.





## Expanders and inapproximability

- We modify this using a 1-expander [Papadimitriou Yannakakis 91]
  - Replace each appearance of variable  $x$  with a fresh variable  $x_1, x_2, \dots, x_n$
  - Construct an  $n$ -vertex 1-expander.
  - For each edge  $(i, j)$  add the clauses  $(x_i \rightarrow x_j) \wedge (x_j \rightarrow x_i)$

# Applications of Expanders

Why does this work?

- Suppose that in the new instance the optimal assignment sets some of the  $x_i$ 's to 0 and others to 1.
- This gives a partition of the 1-expander.
- Each edge cut by the partition corresponds to an unsatisfied clause.
- Number of cut edges  $>$  number of minority assigned vertices = number of clauses lost by being consistent.

Hence, it is always optimal to give the same value to all  $x_i$ 's.

- Also, because expander graphs are sparse, only linear number of clauses added.
- This gives some inapproximability constant.



# Limits of expanders

- Expanders sound useful. But how good expanders can we get?

We want:

- Low degree – few edges
- High expansion (at least 1).

These are conflicting goals!

# Limits of expanders

- Expanders sound useful. But how good expanders can we get?

We want:

- Low degree – few edges
- High expansion (at least 1).

These are conflicting goals!

- The smallest  $\Delta$  for which we currently know we can have expansion 1 is  $\Delta = 6$ . [Bollobás 88]

# Limits of expanders

- Expanders sound useful. But how good expanders can we get?

We want:

- Low degree – few edges
- High expansion (at least 1).

These are conflicting goals!

- The smallest  $\Delta$  for which we currently know we can have expansion 1 is  $\Delta = 6$ . [Bollobás 88]
- Problem:  $\Delta = 6$  is too large,  $\Delta = 5$  probably won't work...



# Amplifiers

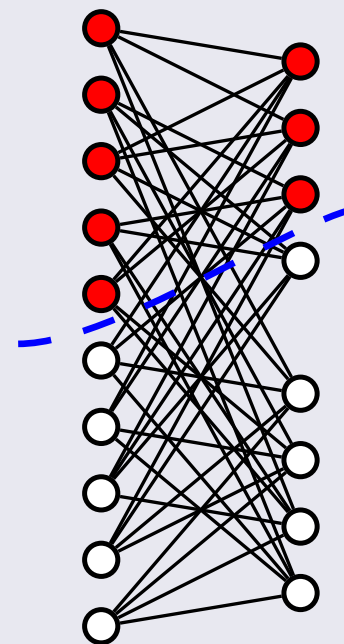
- Amplifiers are expanders for **some of** the vertices.
- The other vertices are thrown in to make consistency easier to achieve.
- This allows us to get smaller  $\Delta$ .

# Amplifiers

- Amplifiers are expanders for **some of** the vertices.
- The other vertices are thrown in to make consistency easier to achieve.
- This allows us to get smaller  $\Delta$ .

## 5-regular amplifier [Berman Karpinski 03]

- Bipartite graph.  $n$  vertices on left,  $0.8n$  vertices on right.
- 4-regular on left, 5-regular on right.
- Graph constructed randomly.
- Crucial Property: whp any partition cuts more edges than the number of **left** vertices on the smaller set.

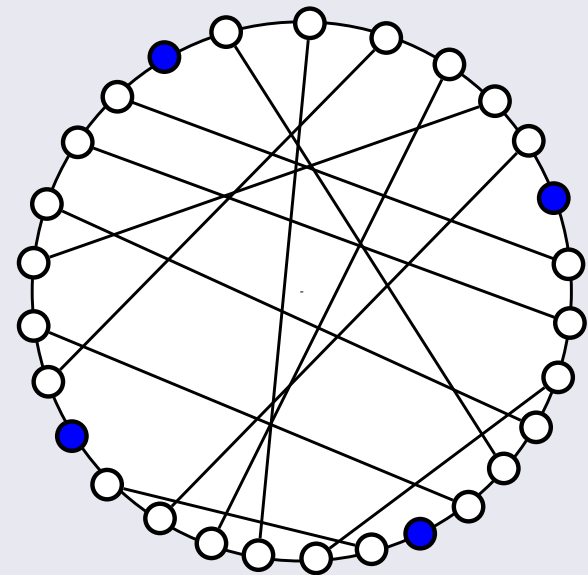


# Amplifiers

- Amplifiers are expanders for **some of** the vertices.
- The other vertices are thrown in to make consistency easier to achieve.
- This allows us to get smaller  $\Delta$ .

3-regular wheel amplifier [Berman Karpinski 01]

- Start with a cycle on  $7n$  vertices.
- Every seventh vertex is a **contact** vertex. Other vertices are checkers.
- Take a random perfect matching of checkers.






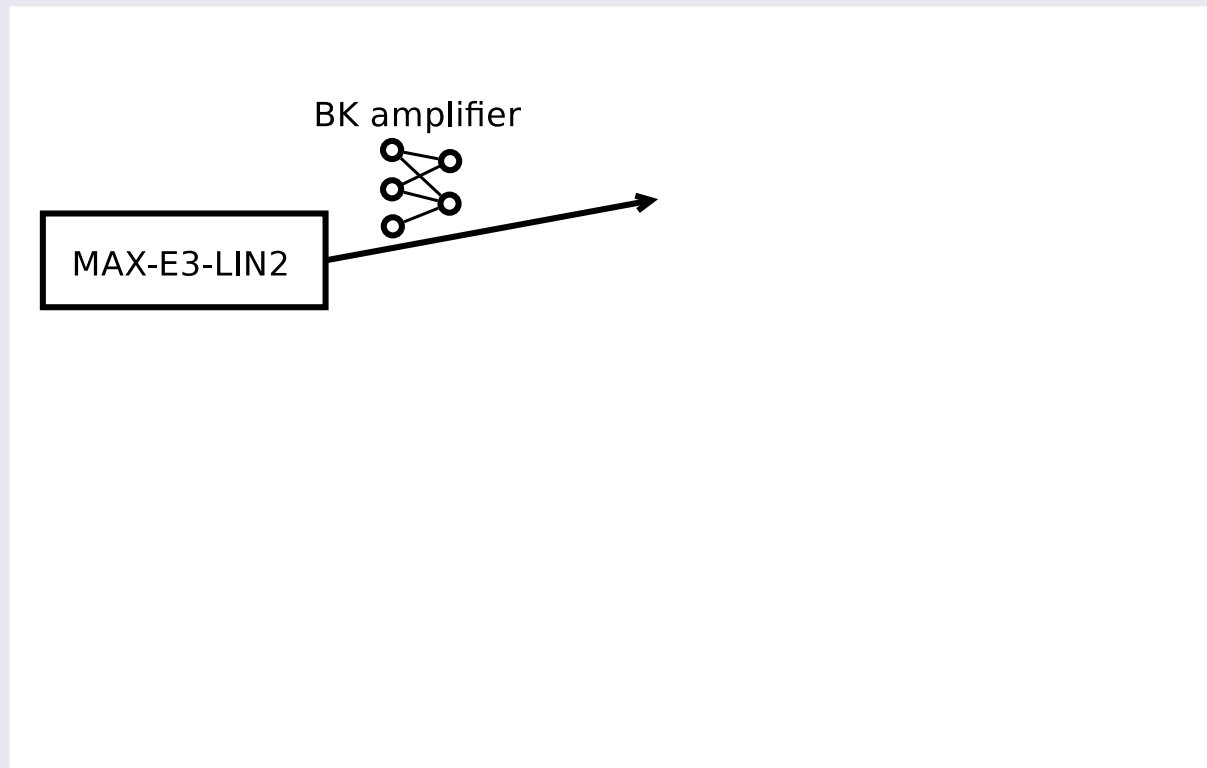
Back to the Reduction

# Overview

MAX-E3-LIN2

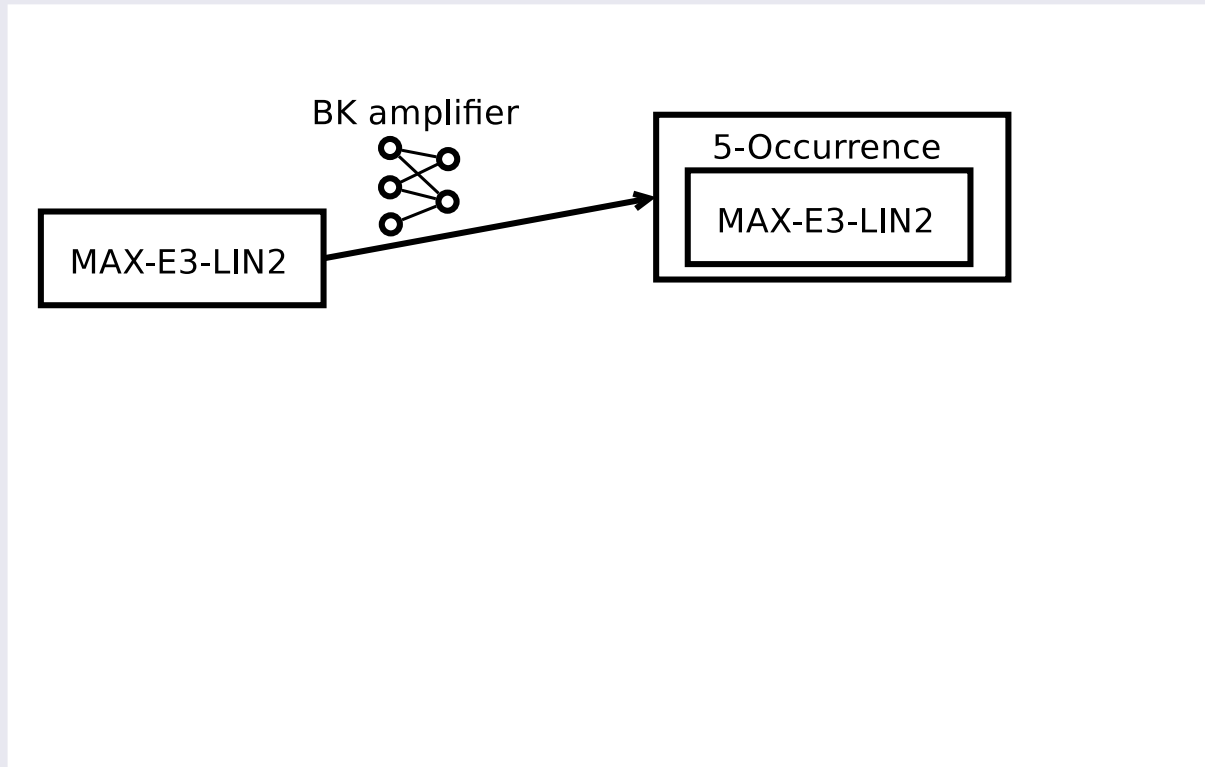
We start from an instance of MAX-E3-LIN2. Given a set of linear equations (mod 2) each of size three satisfy as many as possible. Problem known to be 2-inapproximable (Håstad) 

# Overview

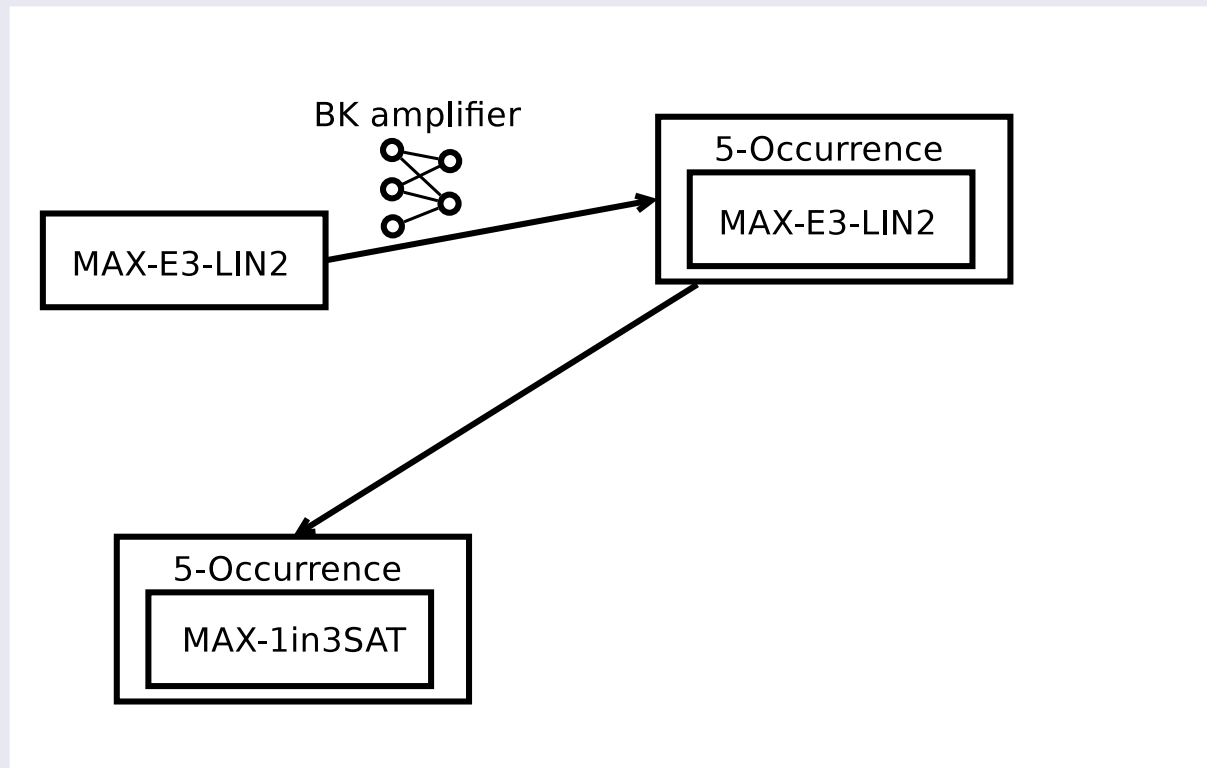


We use the Berman-Karpinski amplifier construction to obtain an instance where each variable appears exactly 5 times (and most equations have size 2).

# Overview

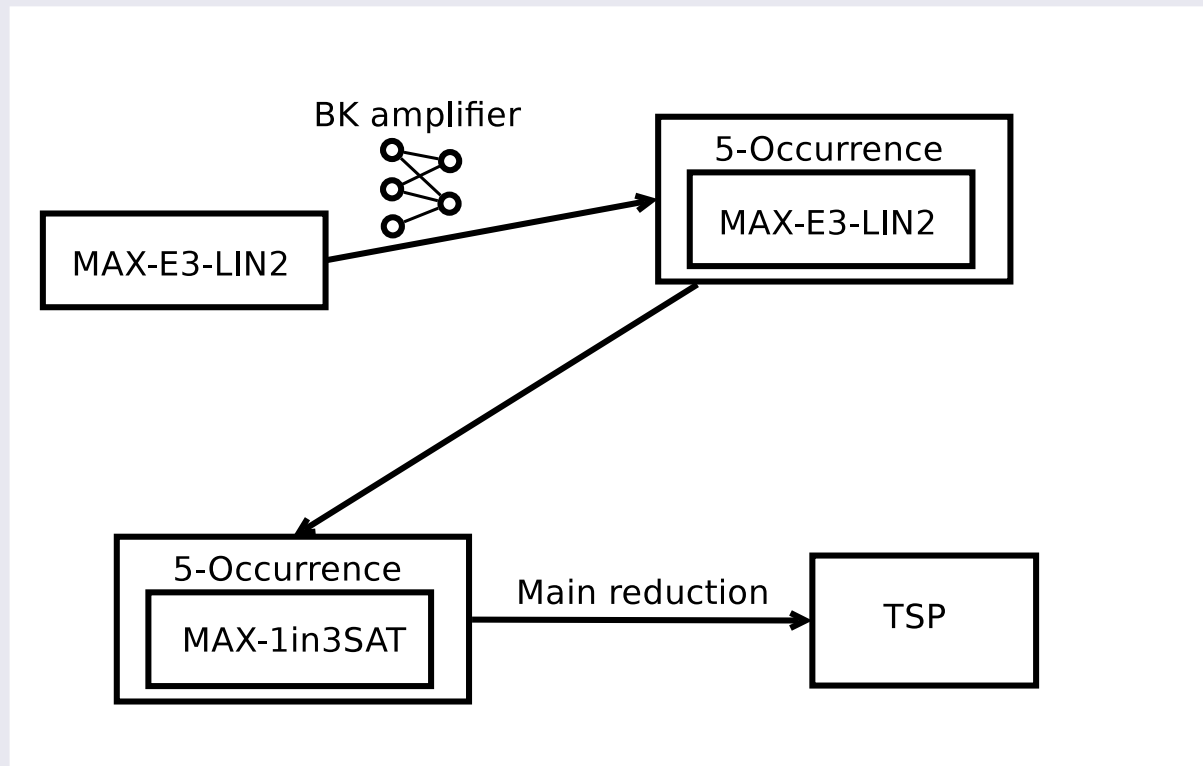


# Overview



A simple trick reduces this to the 1in3 predicate.

# Overview



From this instance we construct a graph.

## Input:

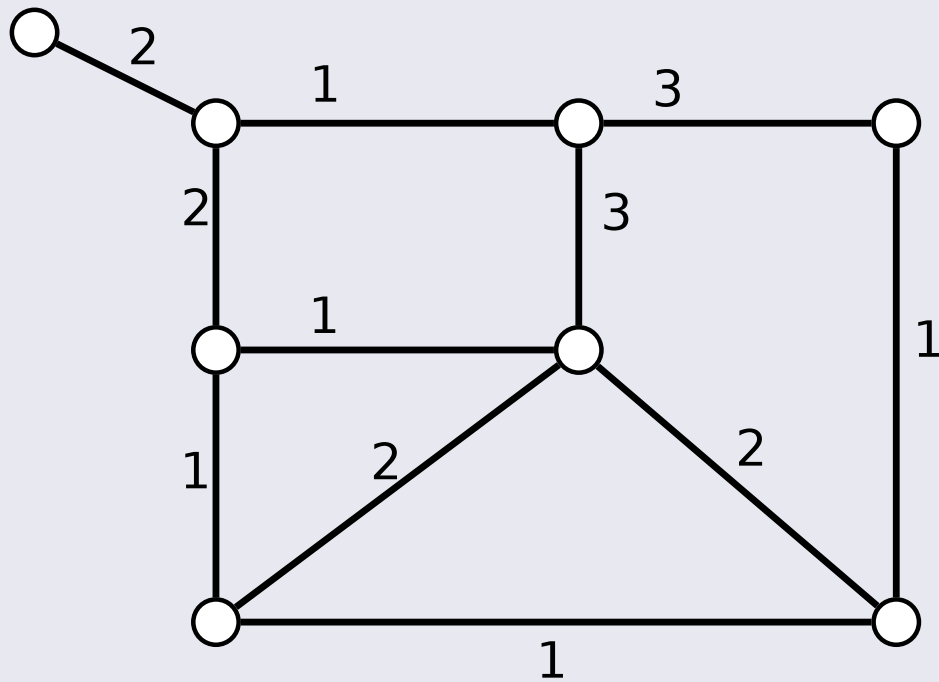
A set of clauses  $(l_1 \vee l_2 \vee l_3)$ ,  $l_1, l_2, l_3$  literals.

## Objective:

A clause is satisfied if **exactly** one of its literals is true. Satisfy as many clauses as possible.

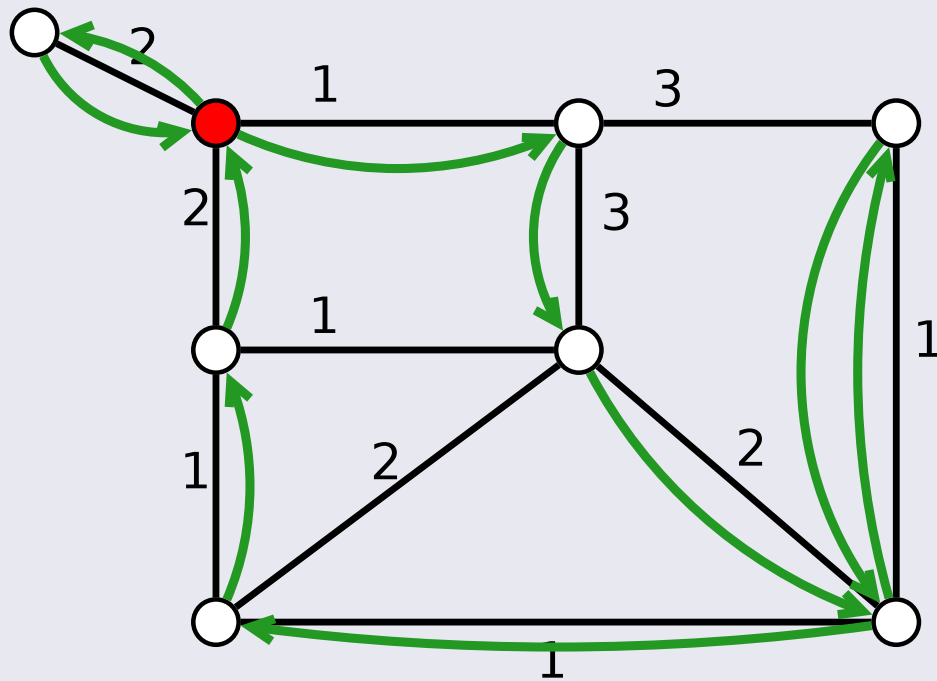
- Easy to reduce MAX-LIN2 to this problem.
  - Especially for size two equations  $(x + y = 1) \leftrightarrow (x \vee y)$ .
- Naturally gives gadget for TSP
  - In TSP we'd like to visit each vertex at least once, but not more than once (to save cost)

# TSP and Euler tours

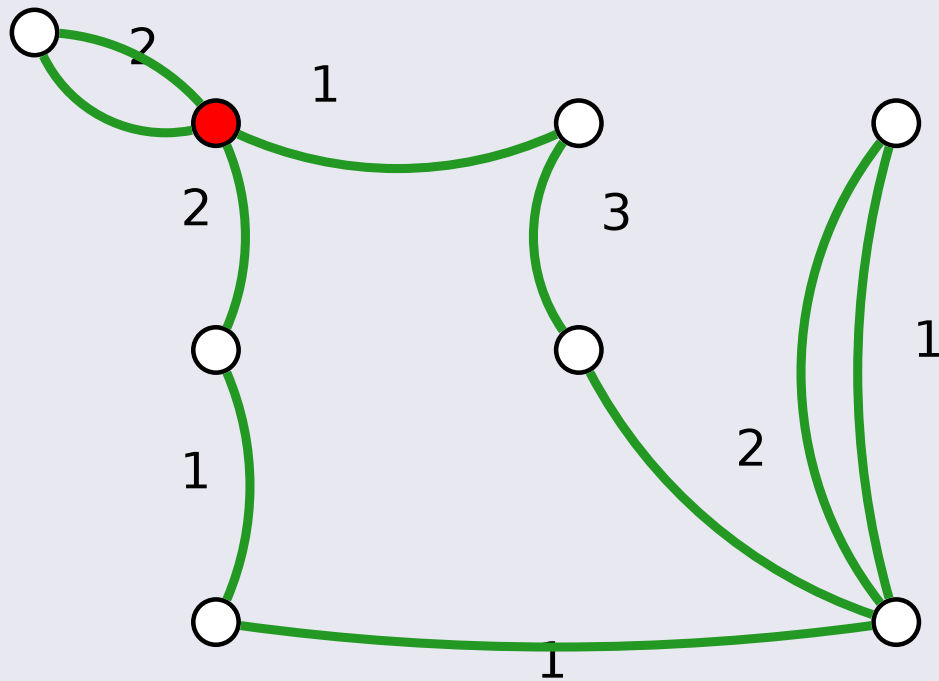




# TSP and Euler tours



# TSP and Euler tours

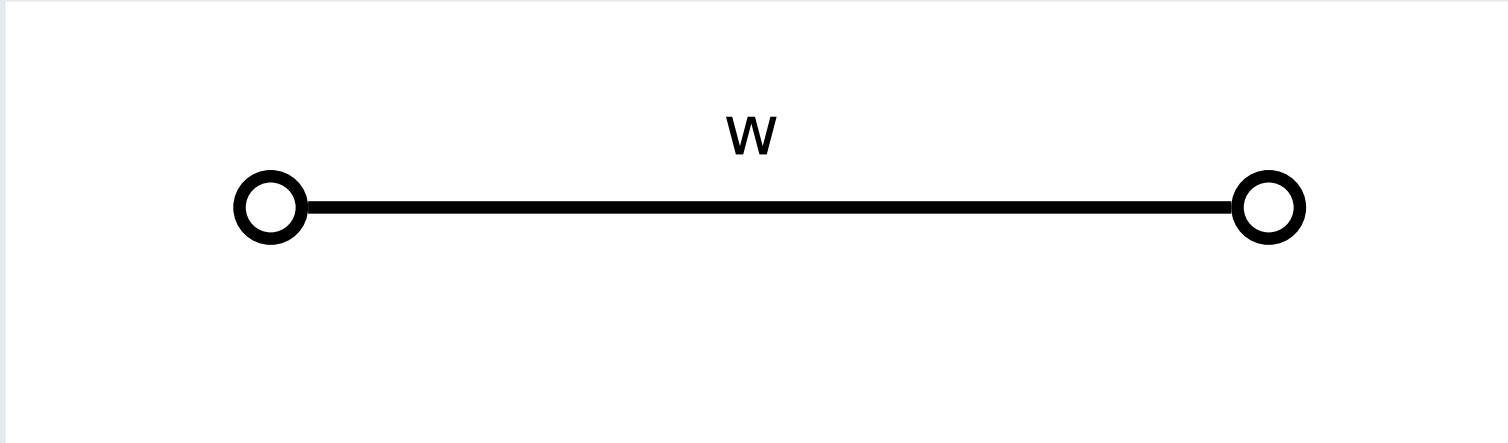


# TSP and Euler tours

- A TSP tour gives an Eulerian multi-graph composed with edges of  $G$ .
- An Eulerian multi-graph composed with edges of  $G$  gives a TSP tour.
  - TSP  $\equiv$  Select a multiplicity for each edge so that the resulting multi-graph is Eulerian and total cost is minimized
  - **Note:** no edge is used more than twice

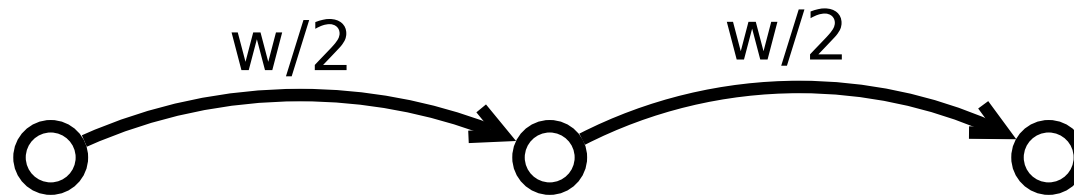


## Gadget – Forced Edges



We would like to be able to dictate in our construction that a certain edge has to be used **at least** once.

## Gadget – Forced Edges



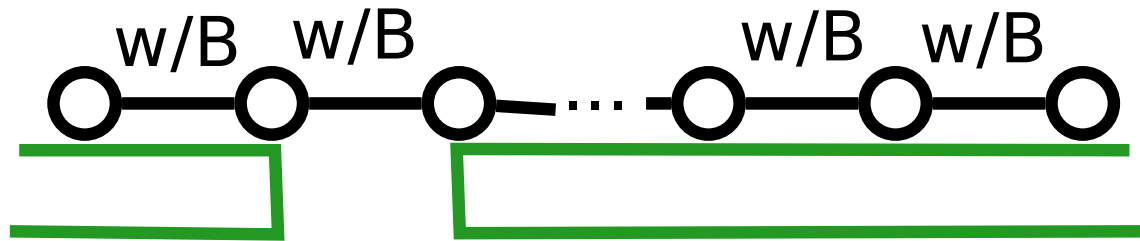
If we had directed edges, this could be achieved by adding a dummy intermediate vertex

## Gadget – Forced Edges



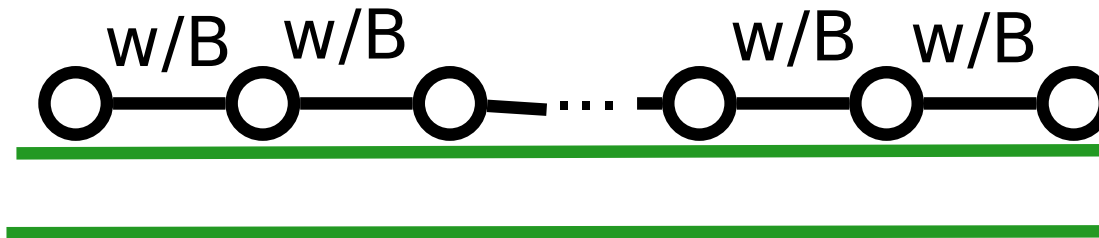
Here, we add many intermediate vertices and evenly distribute the weight  $w$  among them. Think of  $B$  as very large.

# Gadget – Forced Edges



At most one of the new edges may be unused, and in that case all others are used twice.

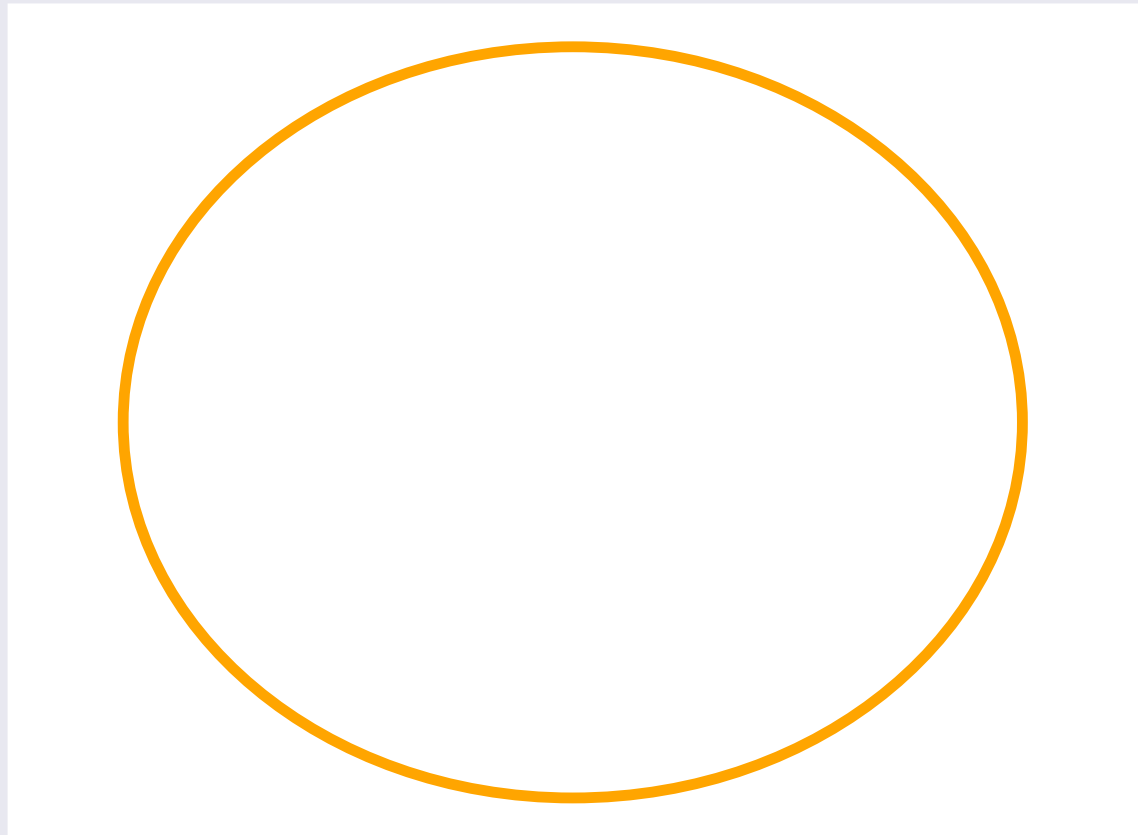
# Gadget – Forced Edges



In that case, adding two copies of that edge to the solution doesn't hurt much (for  $B$  sufficiently large).

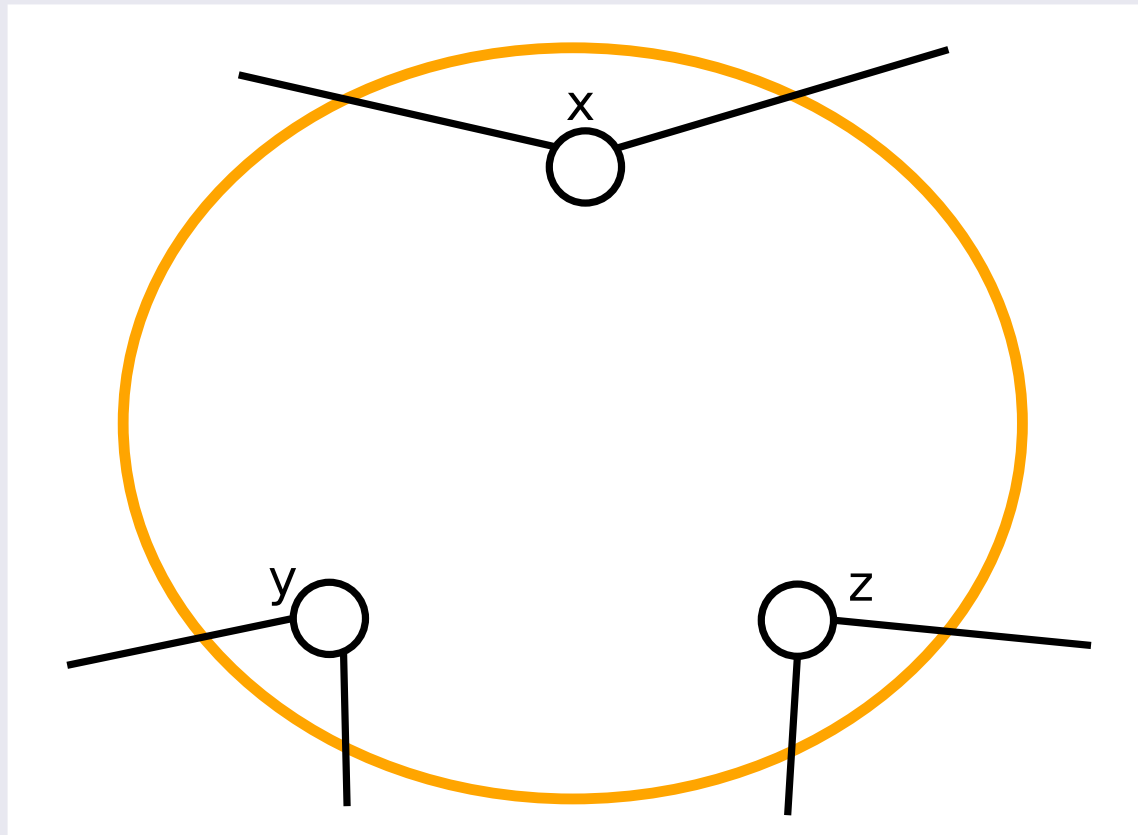


# 1in3 Gadget



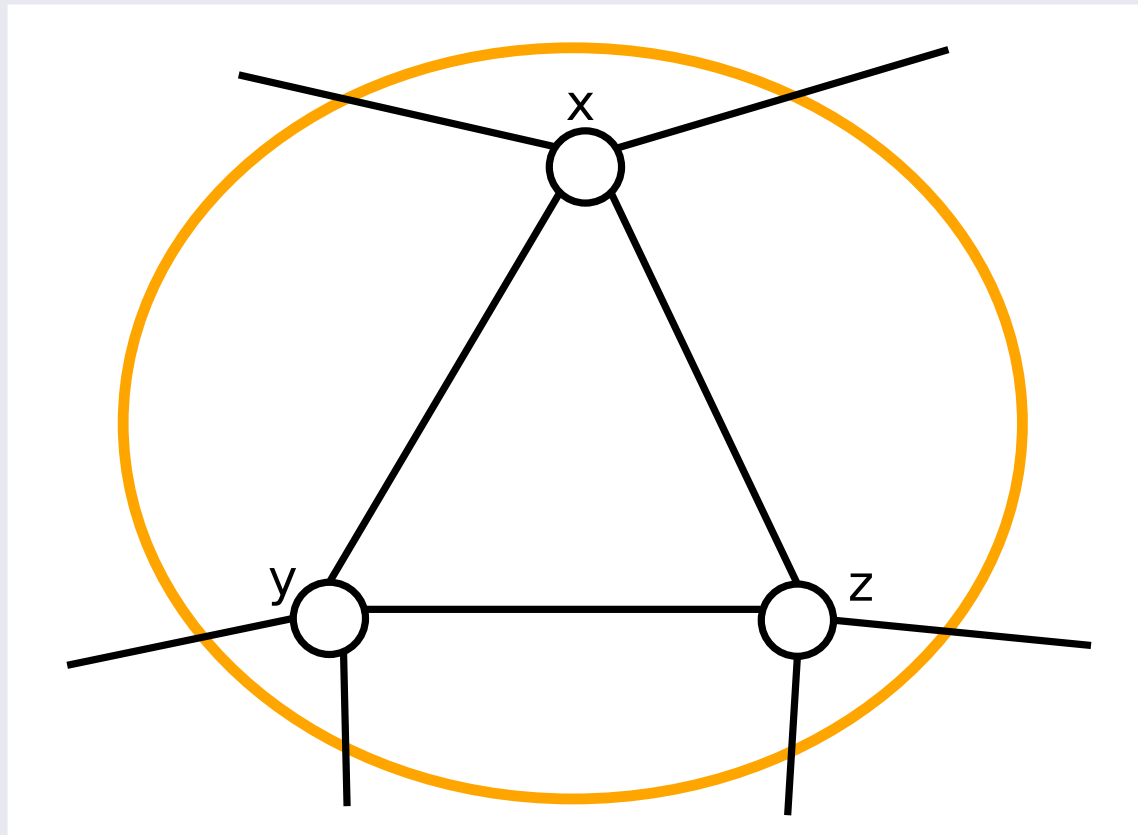
Let's design a gadget  
for  $(x \vee y \vee z)$

# 1in3 Gadget



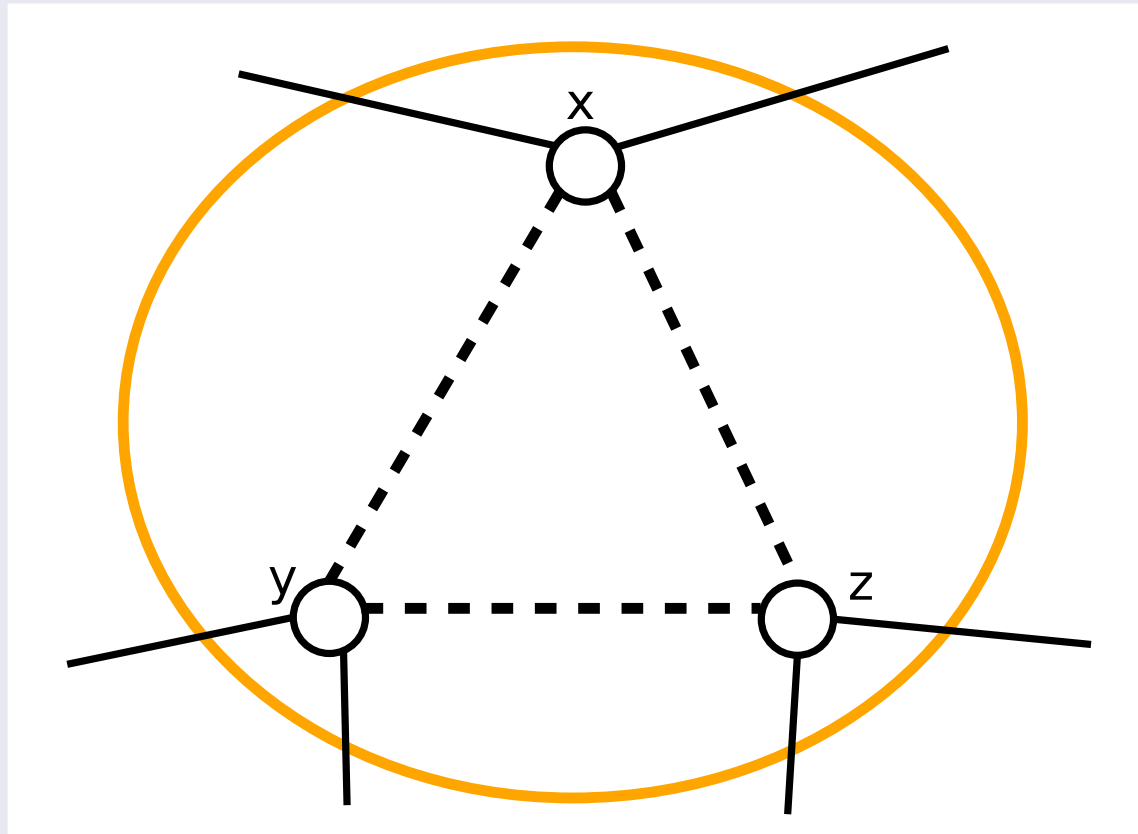
First, three entry/exit points

# 1in3 Gadget



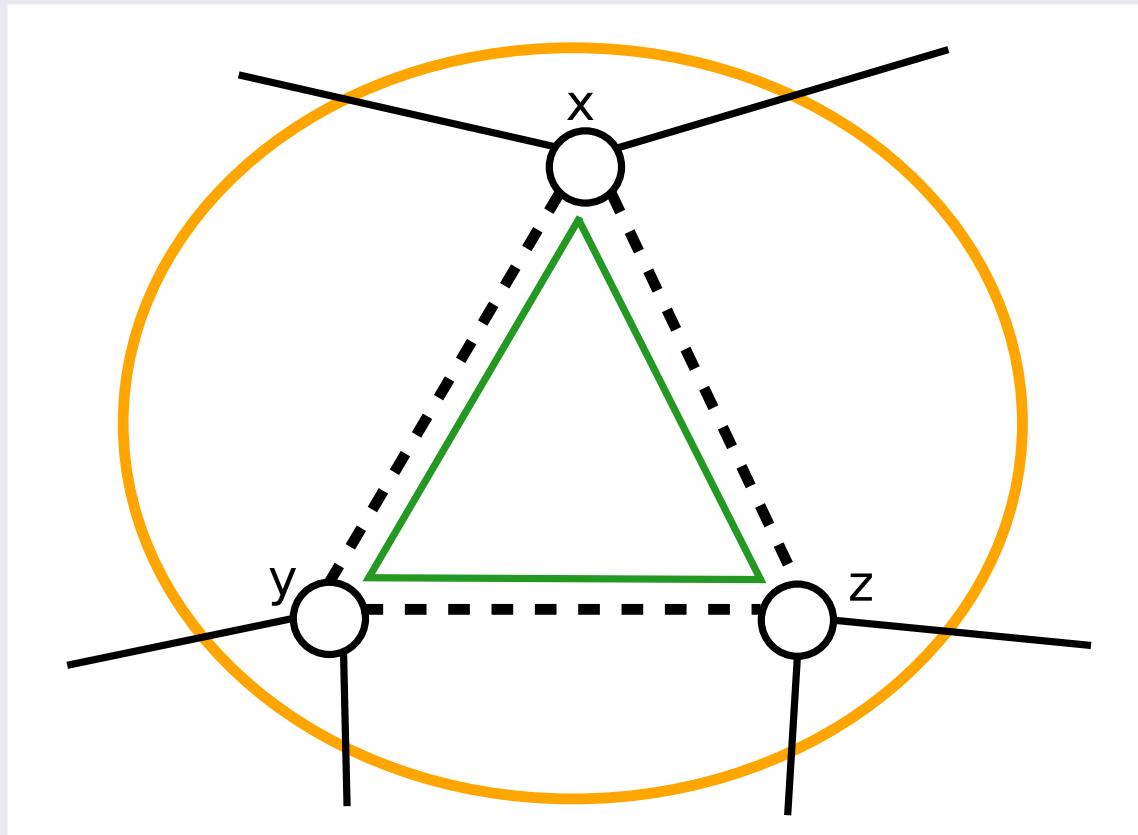
Connect them ...

# 1in3 Gadget



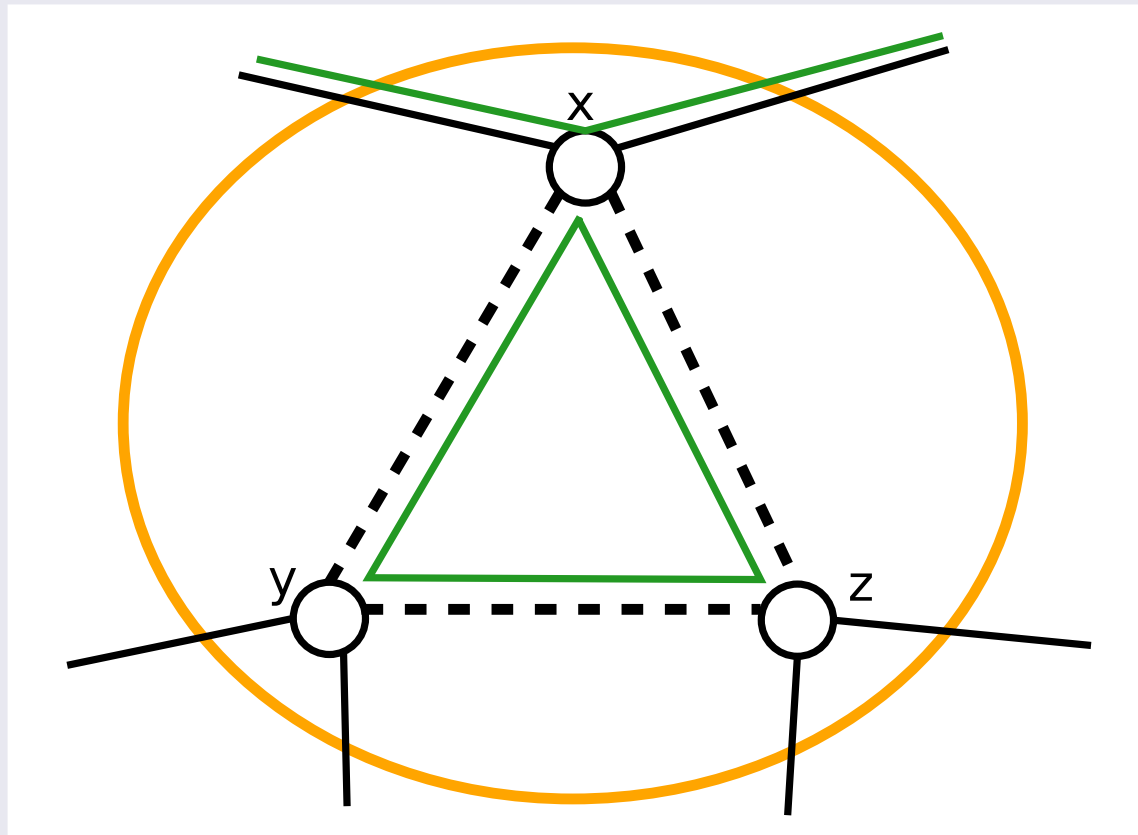
... with forced edges

# 1in3 Gadget



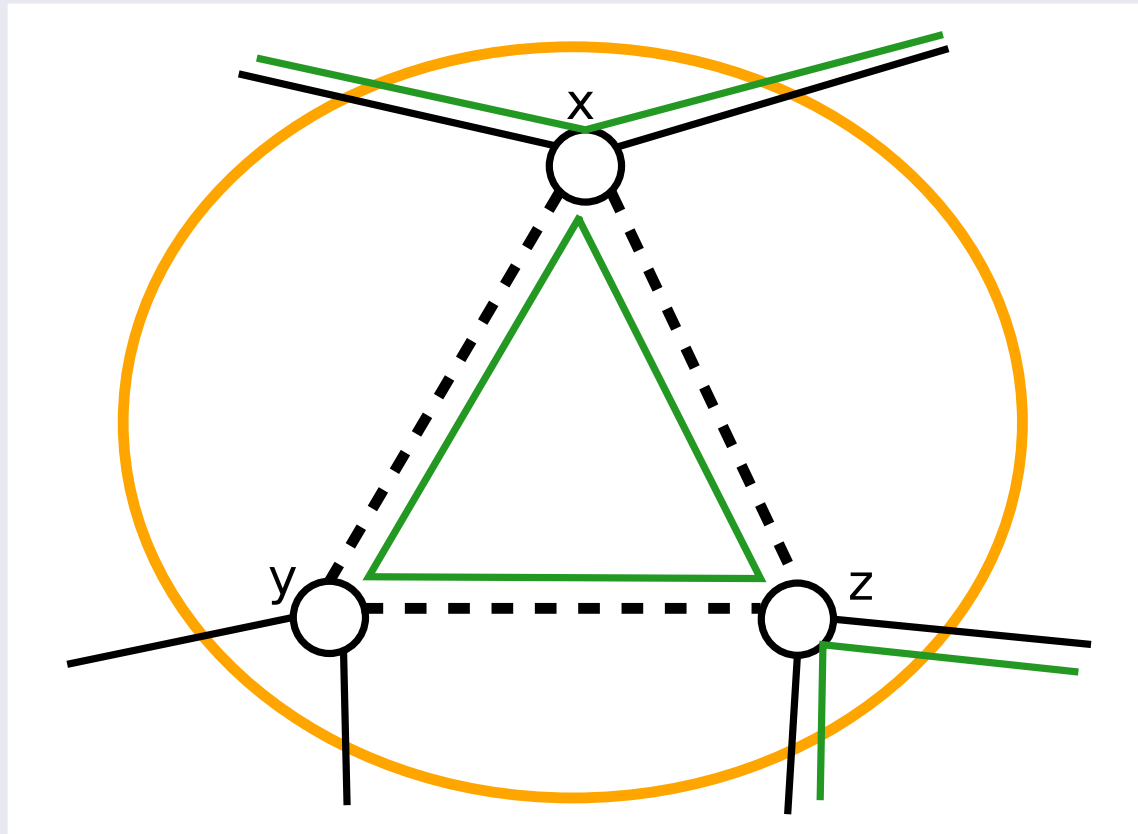
The gadget is a connected component. A good tour visits it once.

# 1in3 Gadget



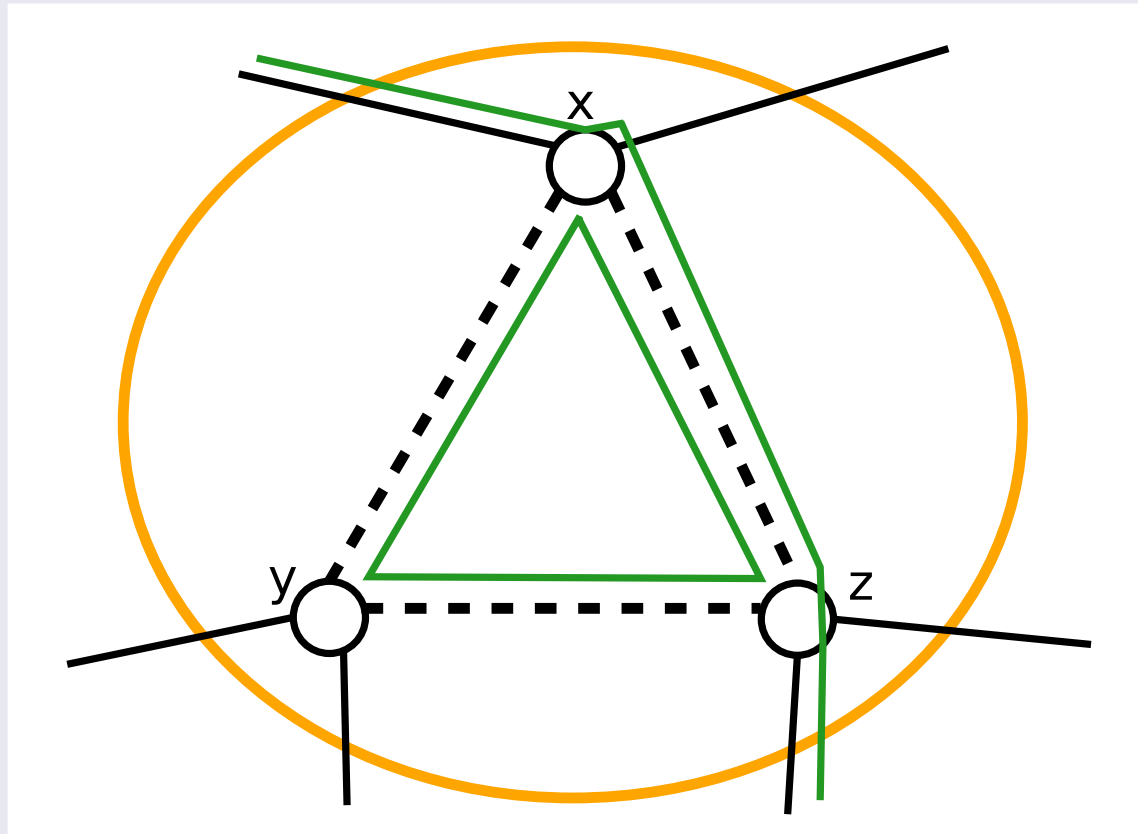
... like this

# 1in3 Gadget



This corresponds to an unsatisfied clause

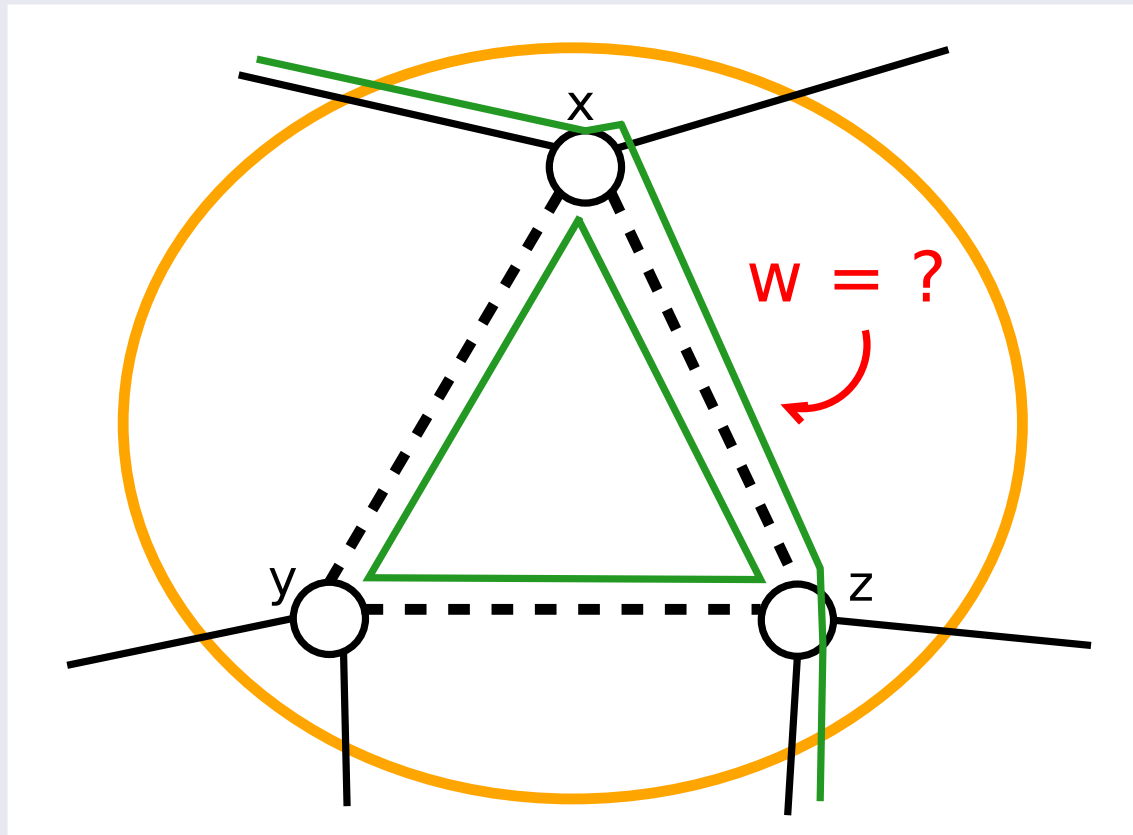
# 1in3 Gadget



This corresponds to a **dishonest** tour



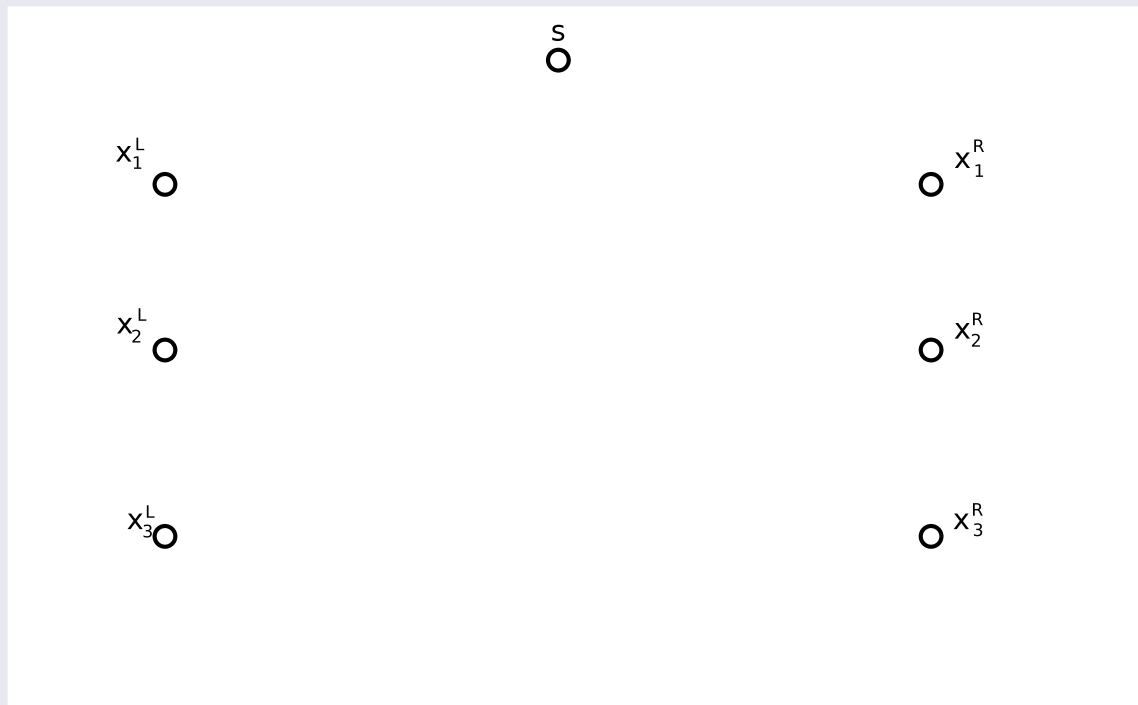
# 1in3 Gadget



The dishonest tour pays this edge twice. How expensive must it be before cheating becomes suboptimal?

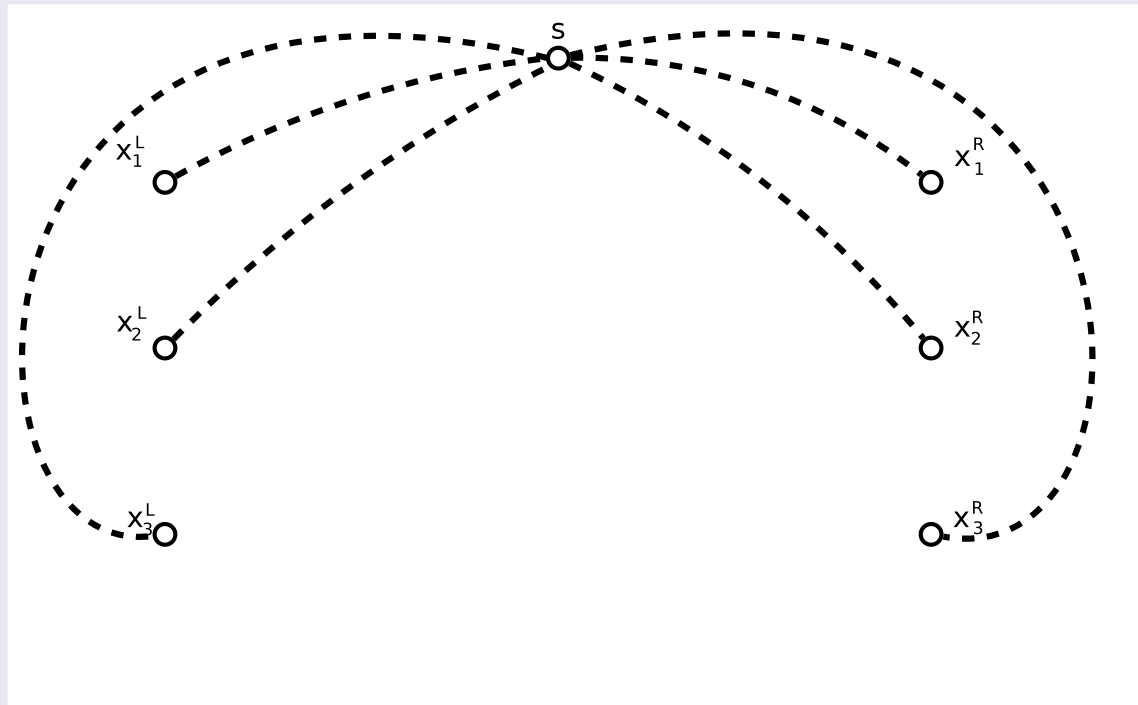
Note that  $w = 10$  suffices, since the two cheating variables appear in at most 10 clauses.

# Construction



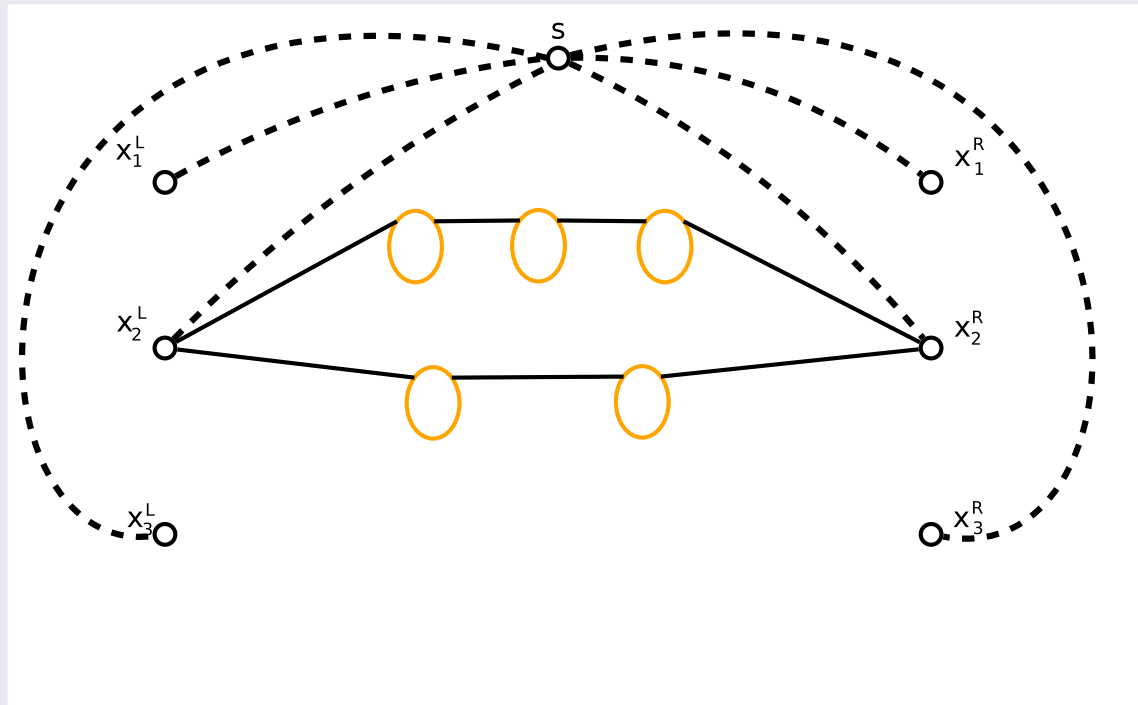
High-level view: construct an origin  $s$  and two terminal vertices for each variable.

# Construction



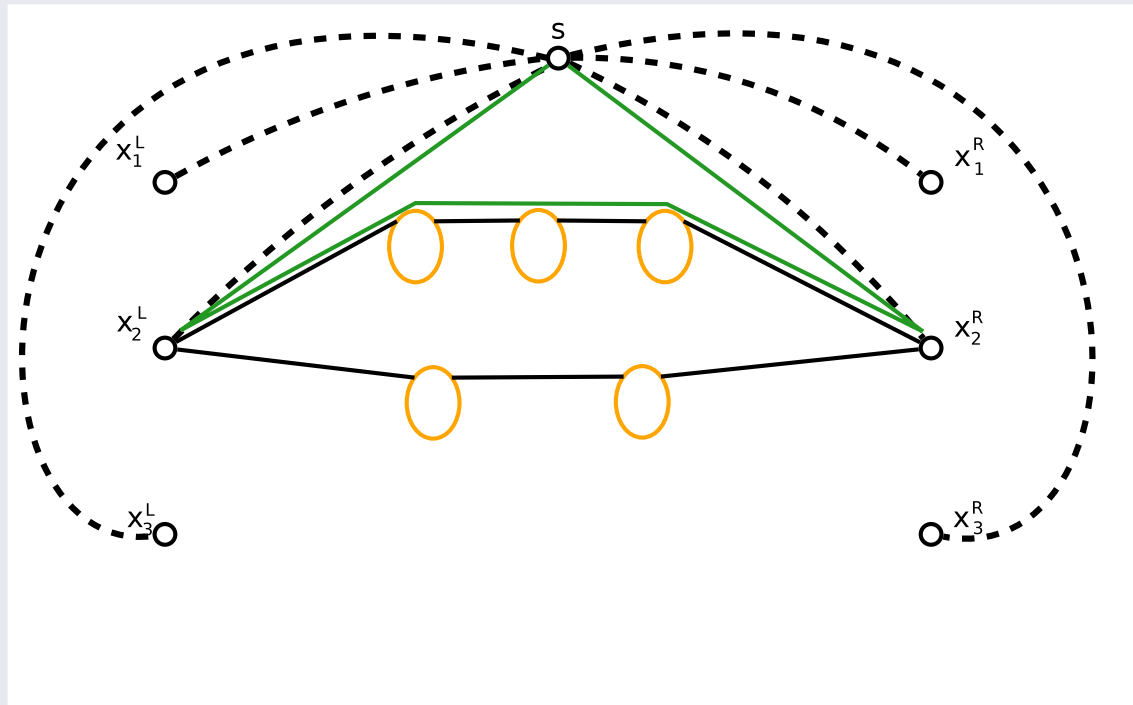
Connect them with forced edges

# Construction



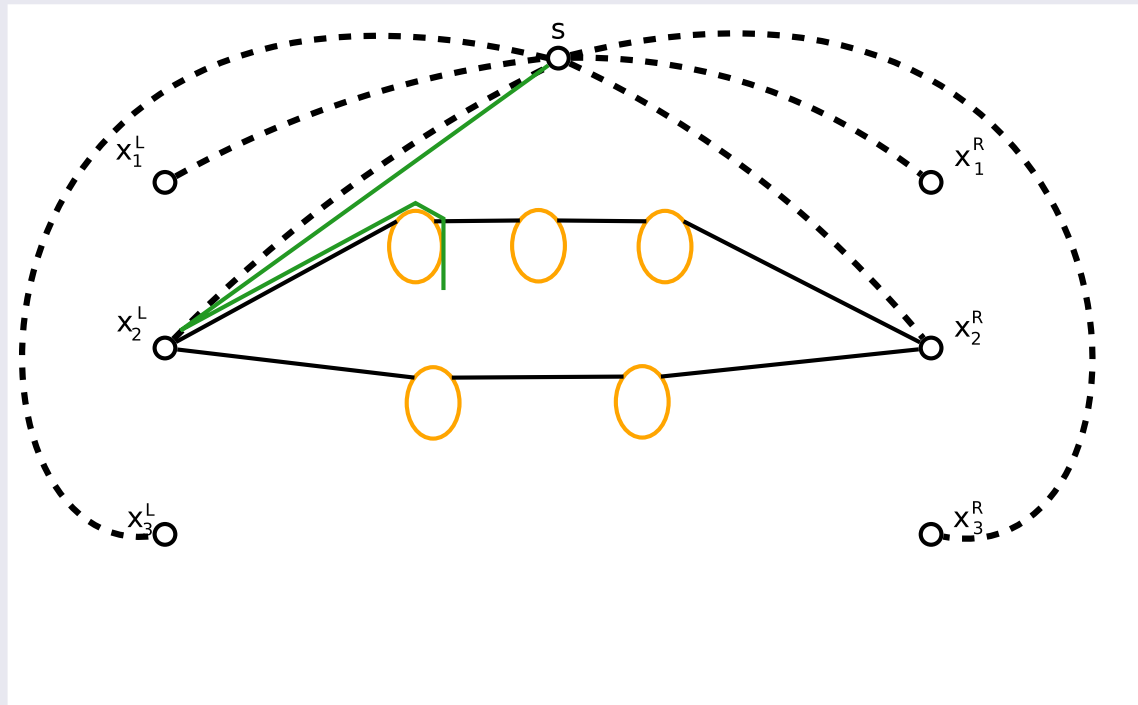
Add the gadgets

# Construction



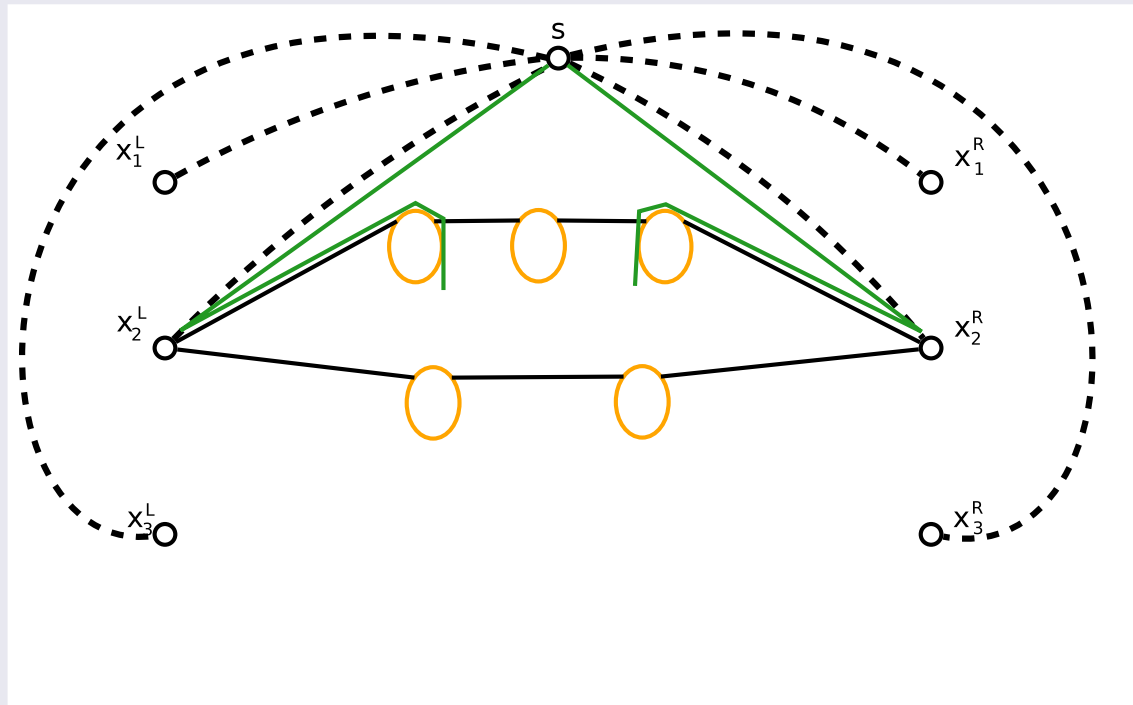
An honest traversal for  $x_2$  looks like this

# Construction



A **dishonest** traversal looks like this...

# Construction

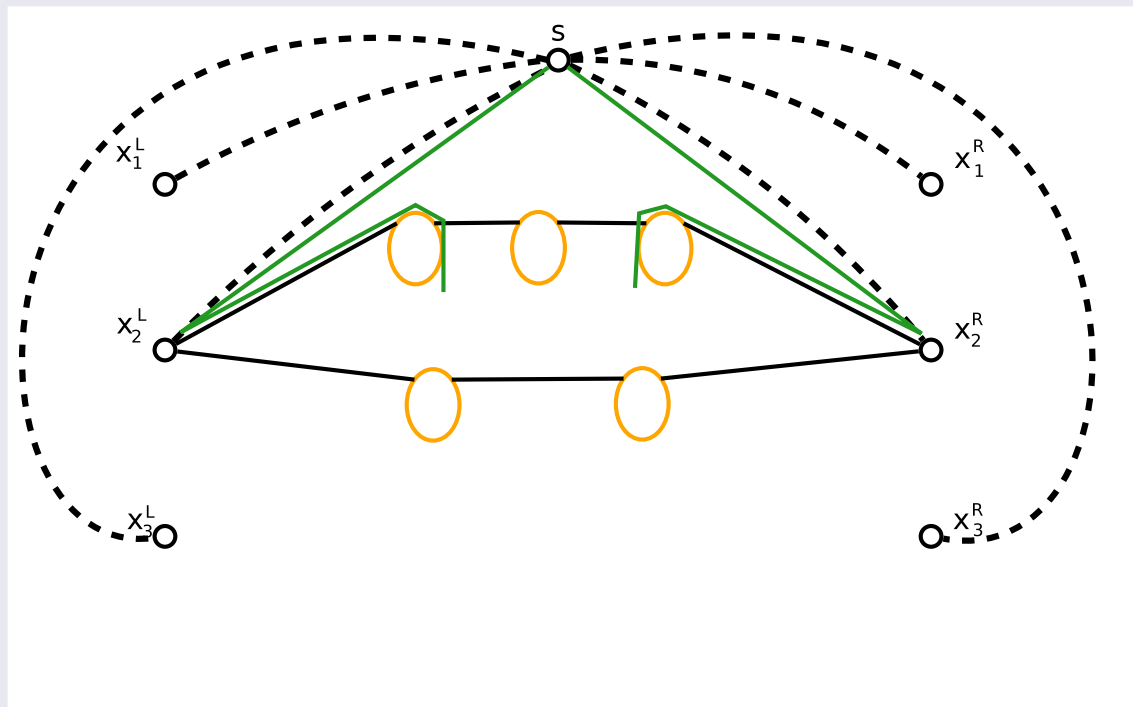


...but there must be cheating in two places

There are as many doubly-used forced edges as affected variables

$$\rightarrow w \leq 5$$

# Construction



...but there must be cheating in two places

There are as many doubly-used forced edges as affected variables

$$\rightarrow w \leq 5$$

In fact, no need to write off affected clauses. Use random assignment for cheated variables and some of them will be satisfied



# Under the carpet

- Many details missing
  - Dishonest variables are set randomly but not independently to ensure that some clauses are satisfied with probability 1.
  - The structure of the instance (from BK amplifier) must be taken into account to calculate the final constant.



# Under the carpet

- Many details missing
  - Dishonest variables are set randomly but not independently to ensure that some clauses are satisfied with probability 1.
  - The structure of the instance (from BK amplifier) must be taken into account to calculate the final constant.



## Theorem:

There is no  $\frac{185}{184}$  approximation algorithm for TSP, unless  $P=NP$ .

# Under the carpet

- Many details missing
  - Dishonest variables are set randomly but not independently to ensure that some clauses are satisfied with probability 1.
  - The structure of the instance (from BK amplifier) must be taken into account to calculate the final constant.



## Theorem:

There is no  $\frac{185}{184}$  approximation algorithm for TSP, unless  $P=NP$ .

Can we do better?

# Under the carpet

- Many details missing
  - Dishonest variables are set randomly but not
  - clau
  - The
  - plifie
  - late



## Theorem:

There is no  $\frac{185}{184}$  approximation algorithm for TSP, unless P = NP.

Can we do better?

# Update

Bounds have recently been improved further!

- $\frac{123}{122}$  for TSP
- $\frac{75}{74}$  for ATSP

(Joint work with Marek Karpinski, Richard Schmied)

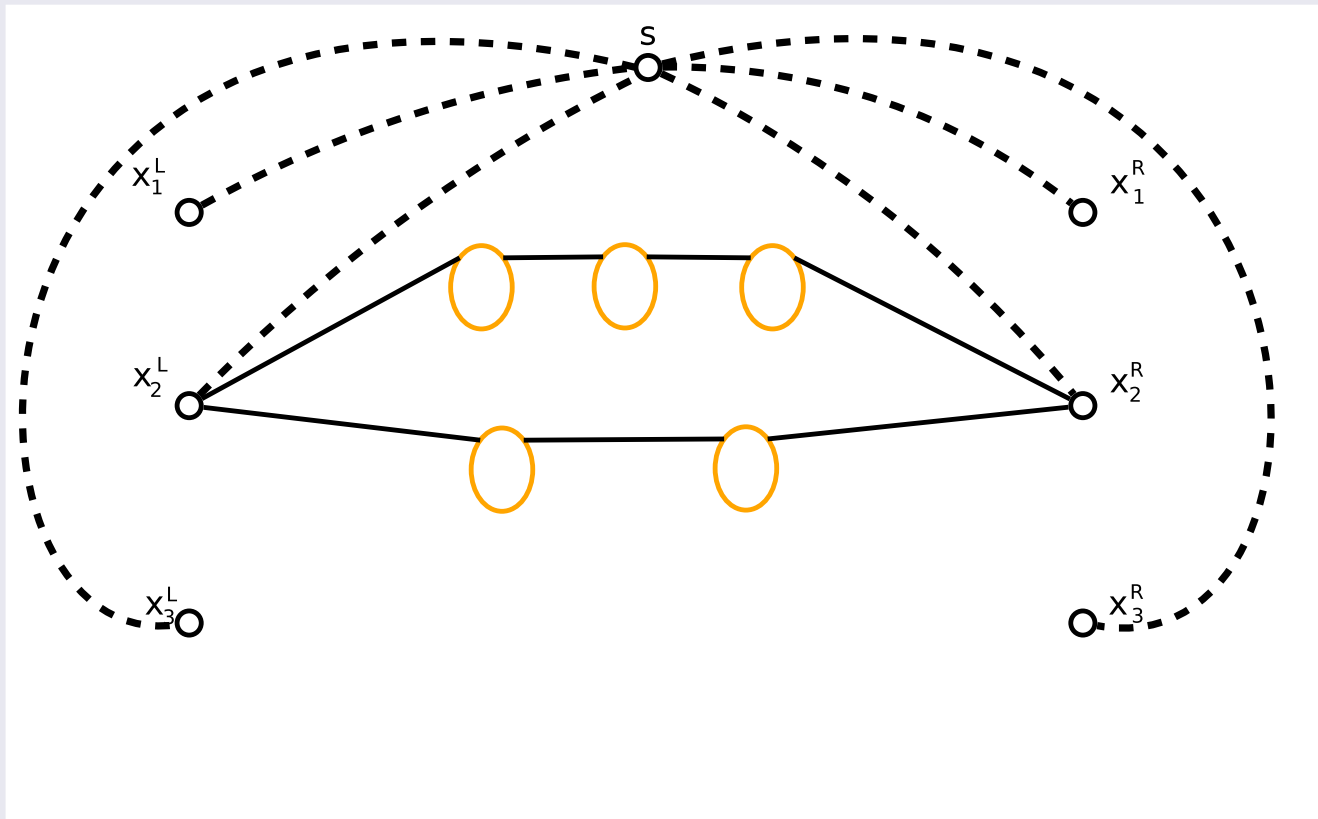
Main ideas:

- Eliminate variable part
- Use 3-regular amplifier
- More clever gadgeteering...



# Lose the variable part

Recall our construction:



The variable part is pure overhead!

# Lose the variable part

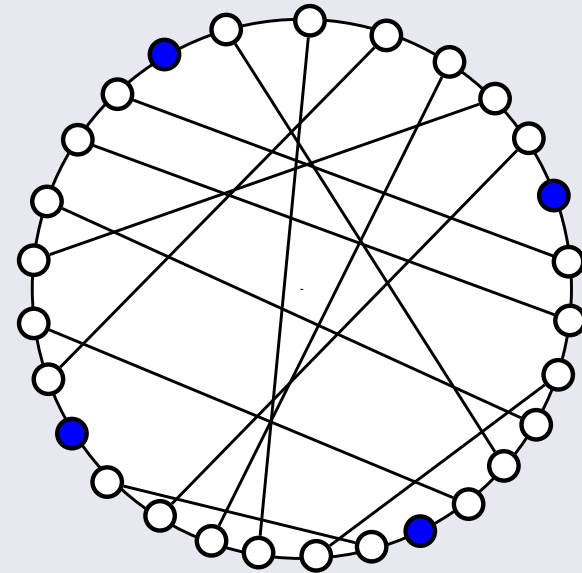
We use an idea that:

- Eliminates this overhead
- Simulates many of the equations of the amplifier “for free”

# Lose the variable part

We use an idea that:

- Eliminates this overhead
- Simulates many of the equations of the amplifier “for free”
- This time we will use the wheel amplifier.
- The idea is to use gadgets only for the matching edges.
- The consistency properties of the gadgets will simulate the cycle edges without extra cost.





# Lose the variable part

Construction summary, CSP  $\rightarrow$  TSP:

- For each variable make a vertex
  - For each cycle edge make an edge
  - Add two gadgets
    - For matching edges
    - For size-three equations
- 
- We are skipping 1-in-3-SAT
  - The wheel and the cycle edges are translated unchanged
  - Matching edges = inequality gadget from previous reduction

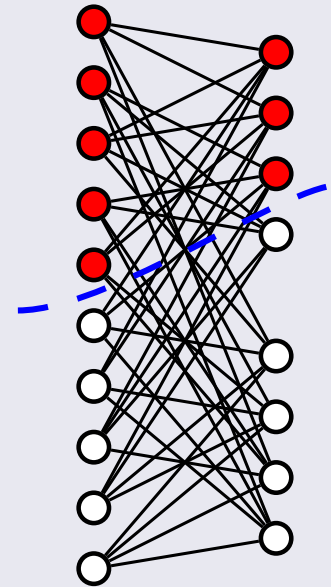


# The problem with inequality

- We want to use an inequality gadget to represent the matching edges of the amplifier.
- Normally, amplifier edges become equalities.

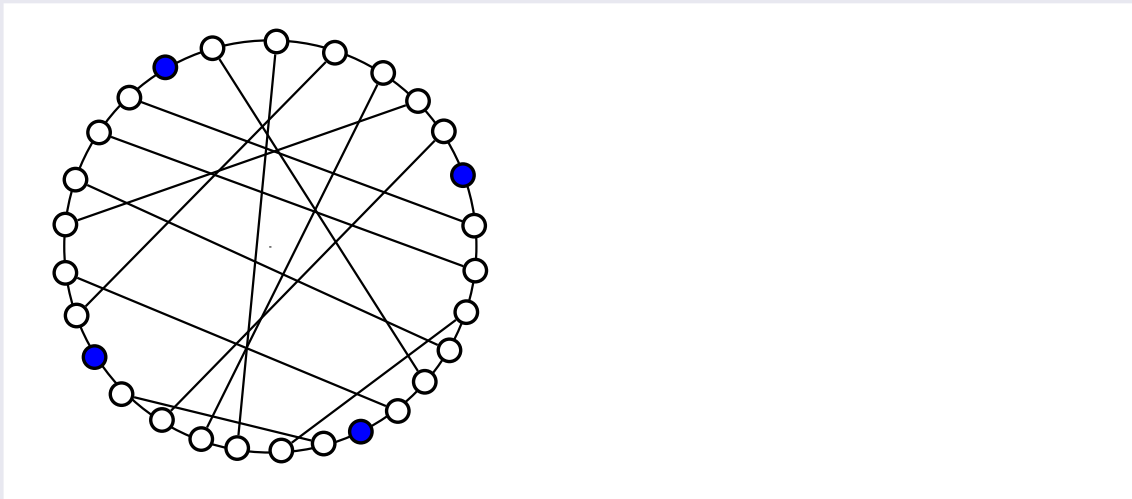
# The problem with inequality

- We want to use an inequality gadget to represent the matching edges of the amplifier.
- Normally, amplifier edges become equalities.
- Replacing them with inequalities is fine for a bipartite amplifier.



# The problem with inequality

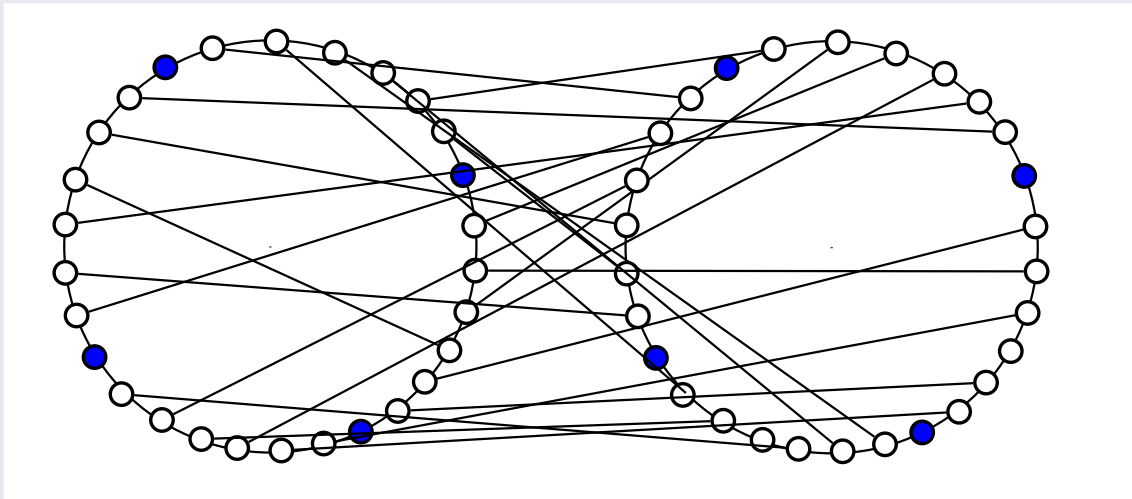
- We want to use an inequality gadget to represent the matching edges of the amplifier.
- Normally, amplifier edges become equalities.



We want cycle edges to remain equalities.

# The problem with inequality

- We want to use an inequality gadget to represent the matching edges of the amplifier.
- Normally, amplifier edges become equalities.



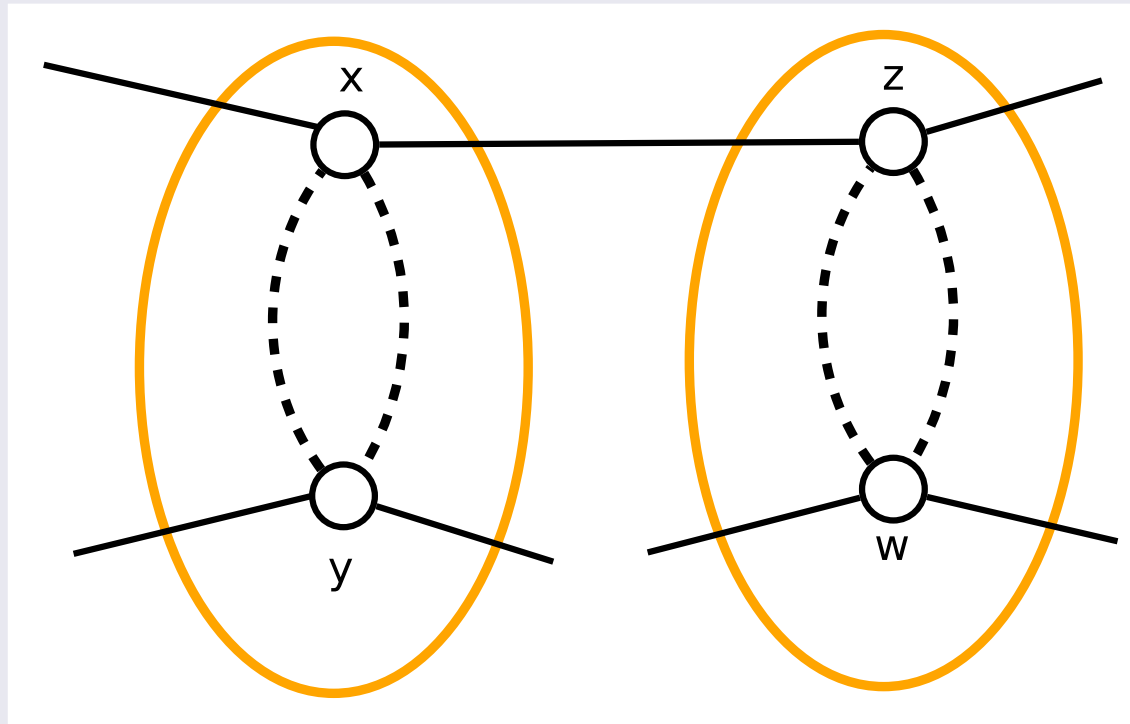
Solution: the bi-wheel!

# Free equations!

Main idea: honesty gives equality

# Free equations!

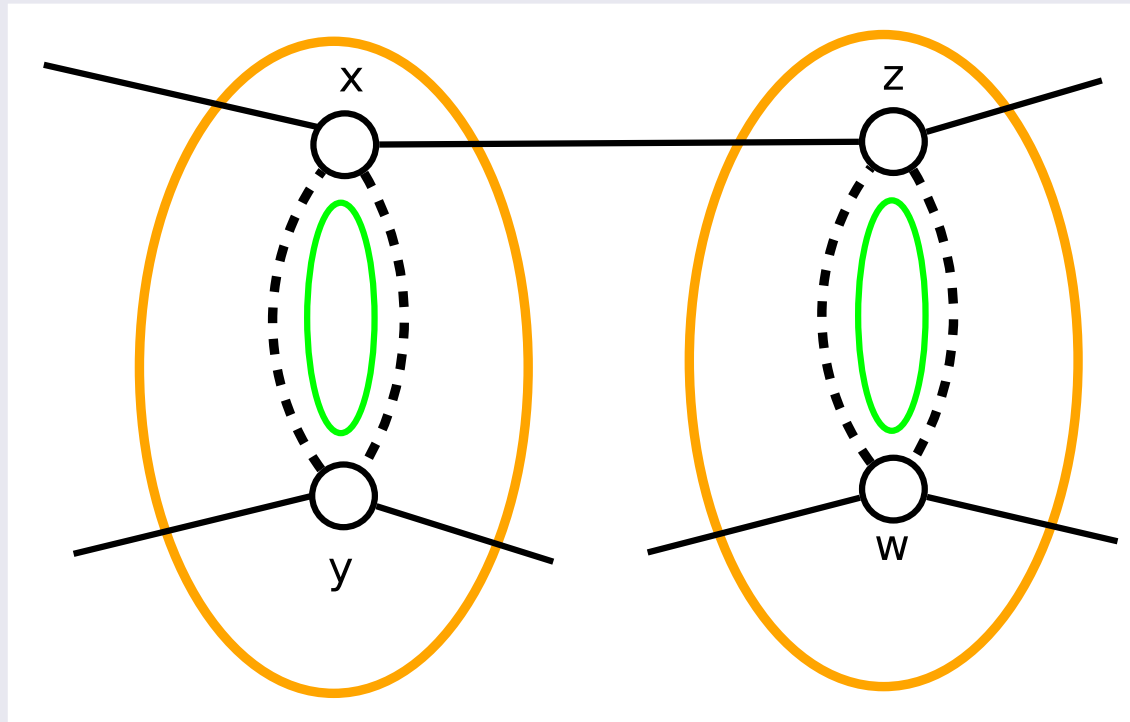
Main idea: honesty gives equality



Consider two vertices consecutive in one cycle  $(x, z)$

# Free equations!

Main idea: honesty gives equality

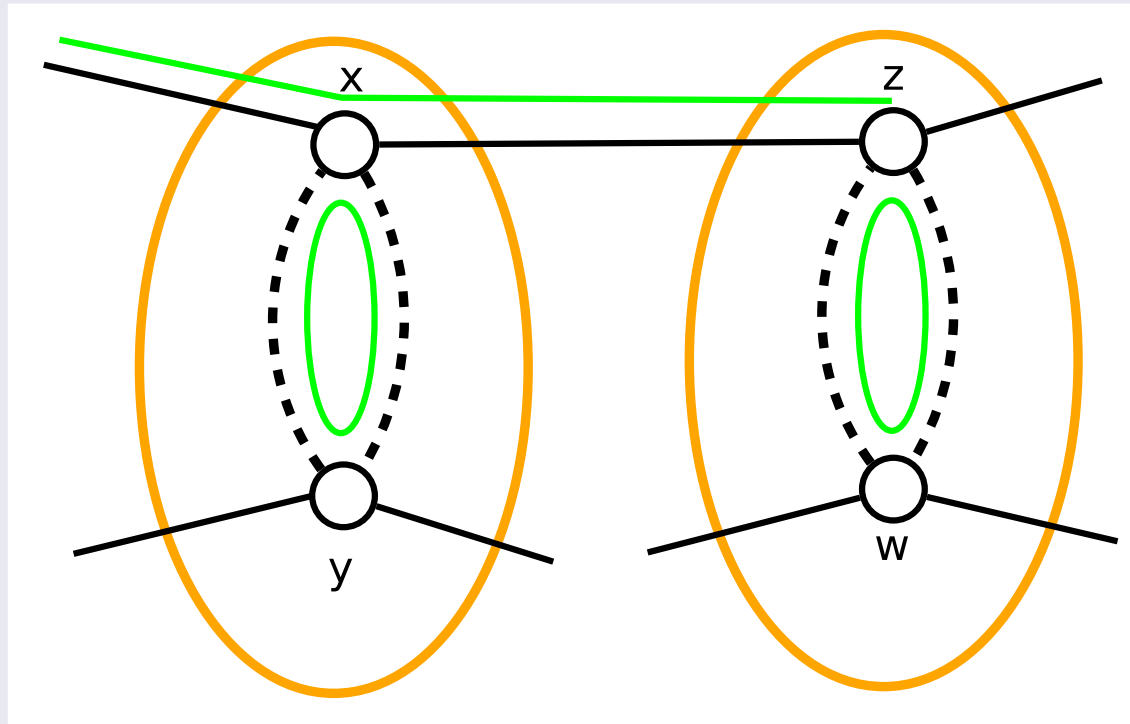


Suppose that their matching gadgets are honest



# Free equations!

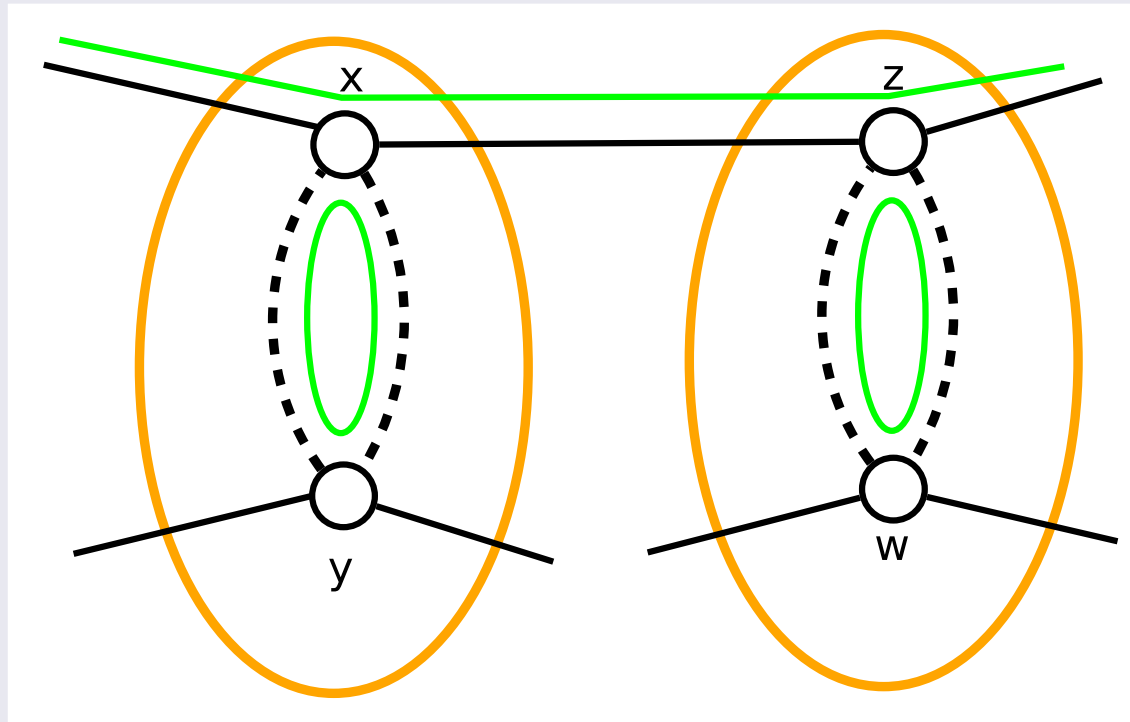
Main idea: honesty gives equality



Then if one is traversed as True...

# Free equations!

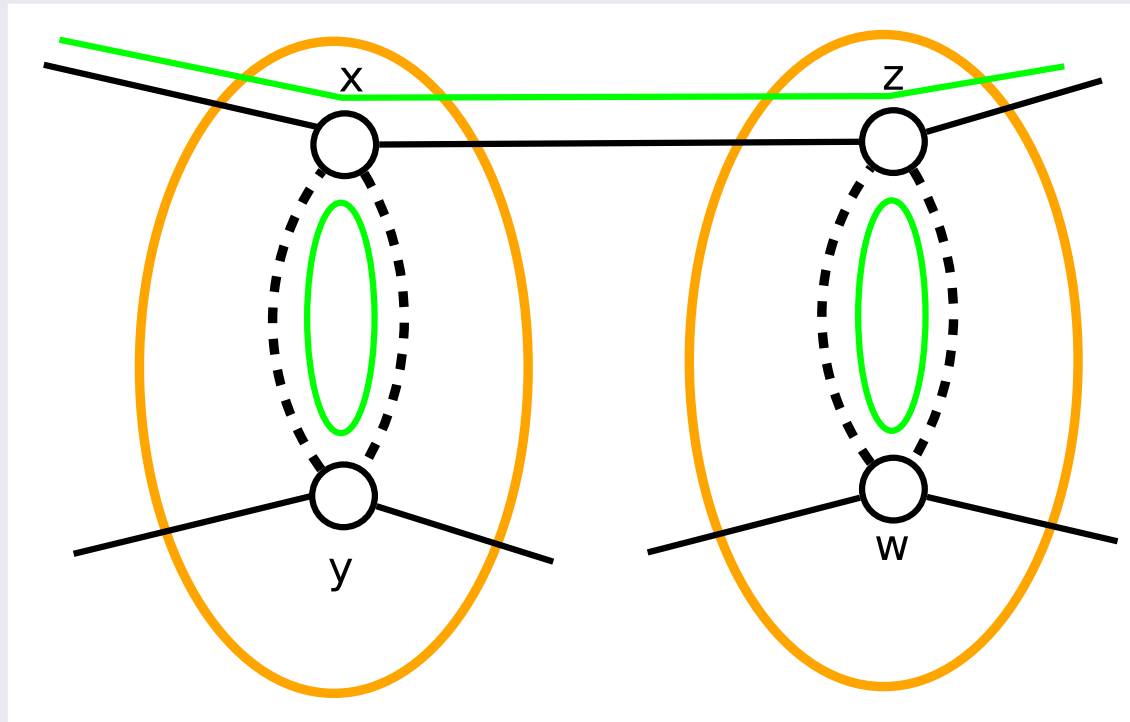
Main idea: honesty gives equality



... the other is also!

# Free equations!

Main idea: honesty gives equality

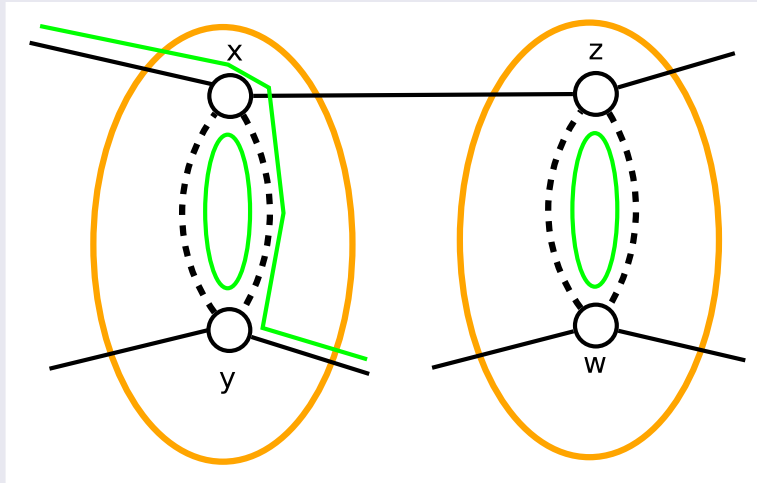


... the other is also!

- In other words, we extract an assignment for  $x$  by setting it to 1 iff both its incident non-forced edges are used.

# Some handwaving

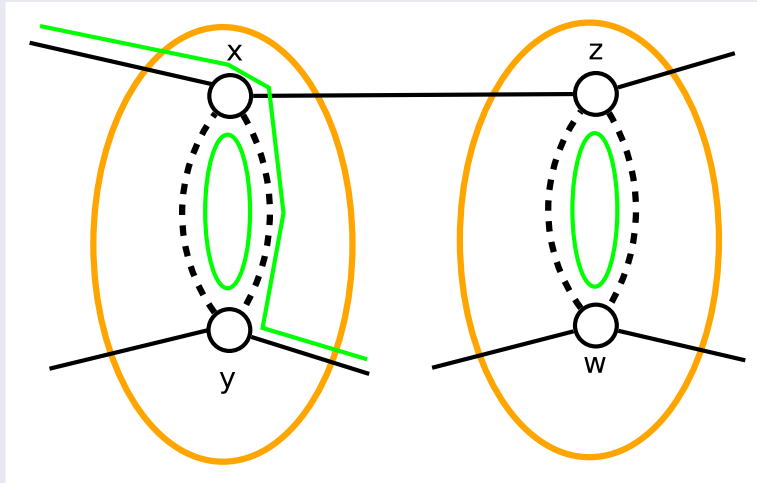
What is the cost of the forced edges?



- In case of dishonest traversal we must make the tour pay for all unsatisfied equations.

# Some handwaving

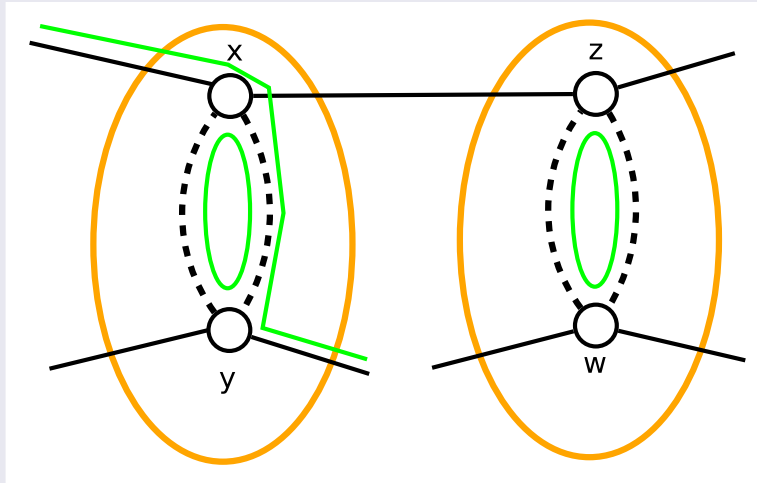
What is the cost of the forced edges?



- In case of dishonest traversal we must make the tour pay for all unsatisfied equations.
- There are 5 affected equation.

# Some handwaving

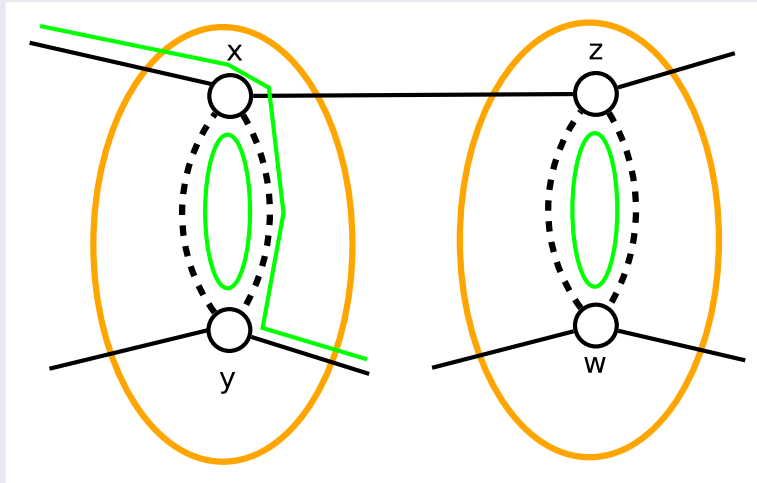
What is the cost of the forced edges?



- In case of dishonest traversal we must make the tour pay for all unsatisfied equations.
- There are 5 affected equation.
- We can always satisfy 3.

# Some handwaving

What is the cost of the forced edges?



- In case of dishonest traversal we must make the tour pay for all unsatisfied equations.
- There are 5 affected equation.
- We can always satisfy 3.
- Hence, cost of forced edges is 2.

# More handwaving

- For size-three equations we come up with some gadget (not shown).
- Some work needs to be done to ensure connectivity.
- Similar ideas can be used for ATSP.





# More handwaving

- For size-three equations we come up with some gadget (not shown).
- Some work needs to be done to ensure connectivity.
- Similar ideas can be used for ATSP.



## Theorem:

There is no  $\frac{123}{122} - \epsilon$  approximation algorithm for TSP, unless  $P=NP$ .

There is no  $\frac{75}{74} - \epsilon$  approximation algorithm for ATSP, unless  $P=NP$ .

# Conclusions – Open problems

- A simpler reduction for TSP and a better inapproximability threshold
  - But, constant still very low!

## Future work

- Better amplifier constructions?
- Application for improved expanders?

# Conclusions – Open problems

- A simpler reduction for TSP and a better inapproximability threshold
  - But, constant still very low!

## Future work

- Better amplifier constructions?
- Application for improved expanders?
- ... **Reasonable** inapproximability for TSP?

# The end



Questions?