

Locality in Networks

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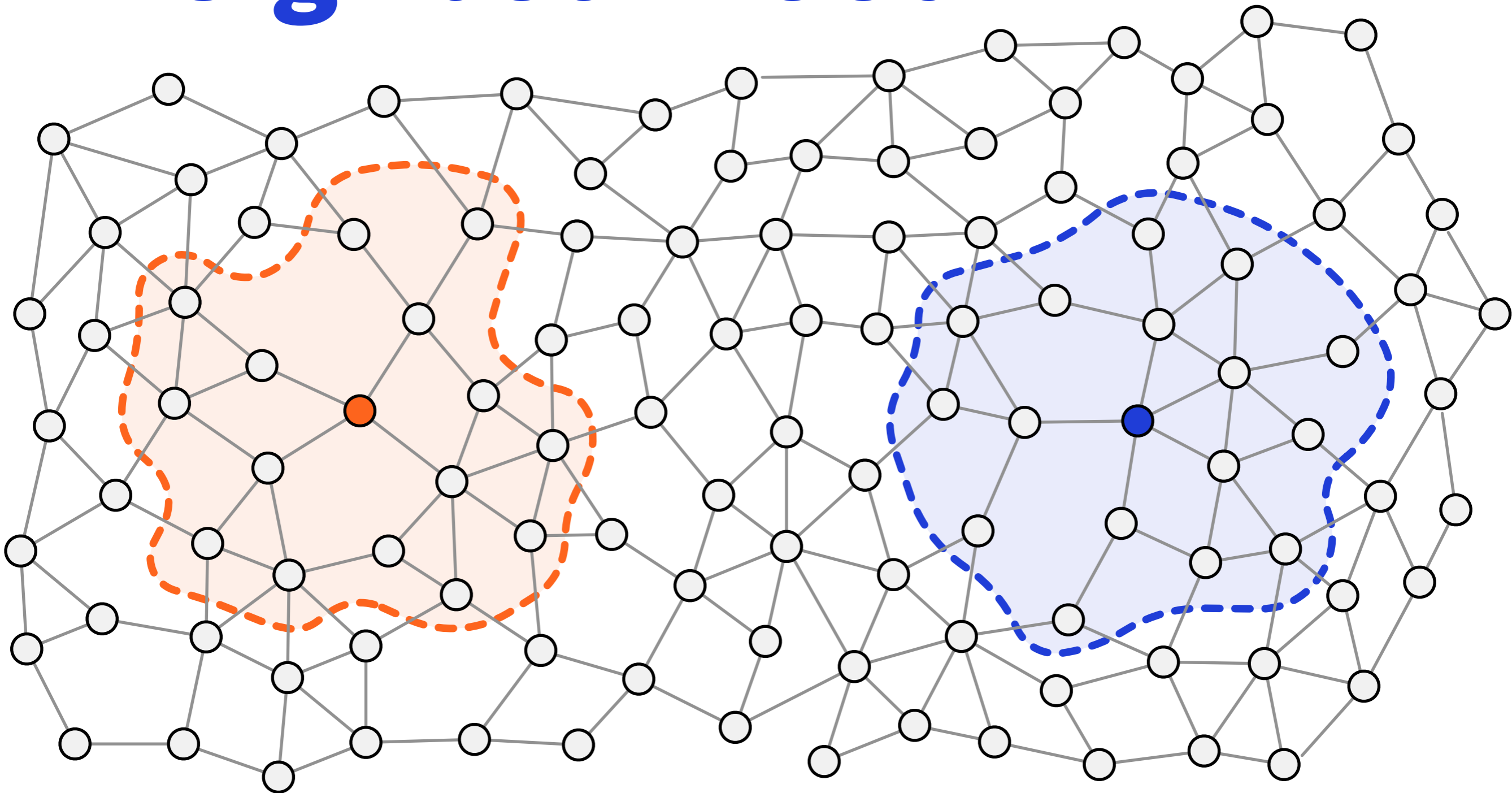
1. Locality and Local Algorithms

– brief introduction

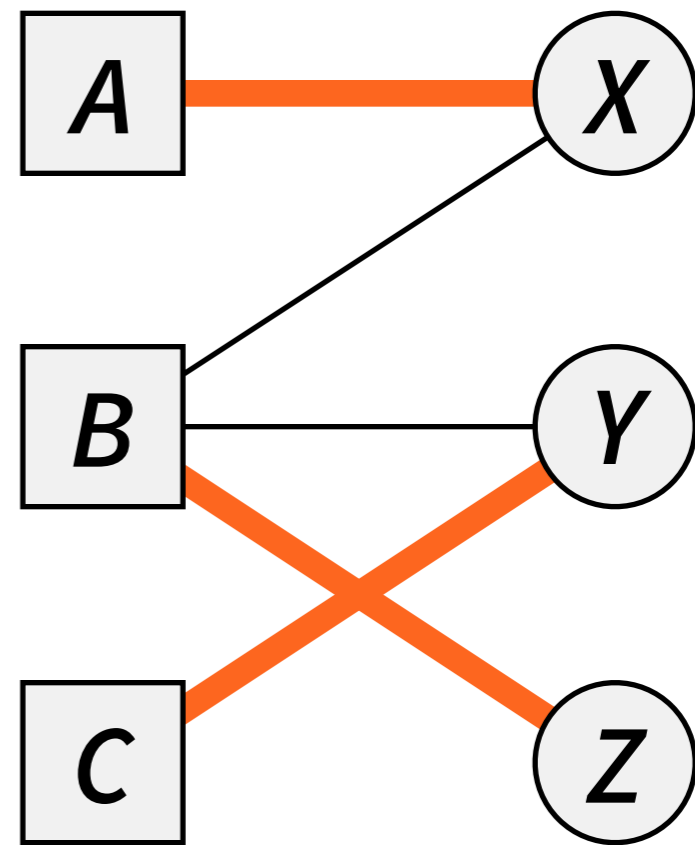
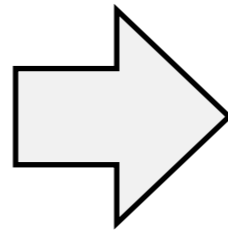
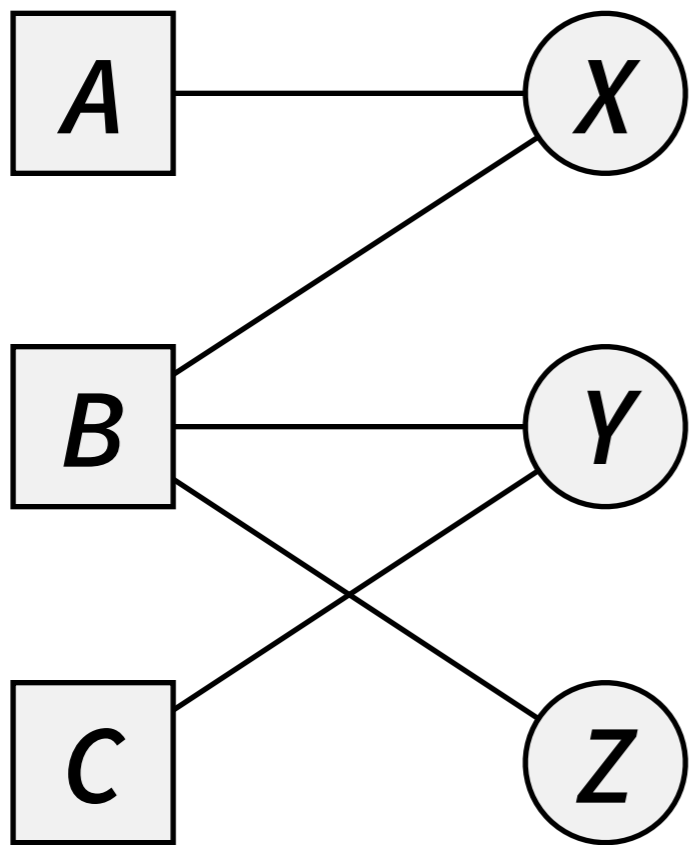
Locality in Networks

- **Basic setting:**
 - nodes act based on **local information only**
 - behaviour of node v = function of information available in $O(1)$ -radius neighbourhood of v
- **Question:**
 - what tasks can be solved?

Constant-Radius Neighbourhood



Example: Matching in Networks



Example:

Matching in Networks

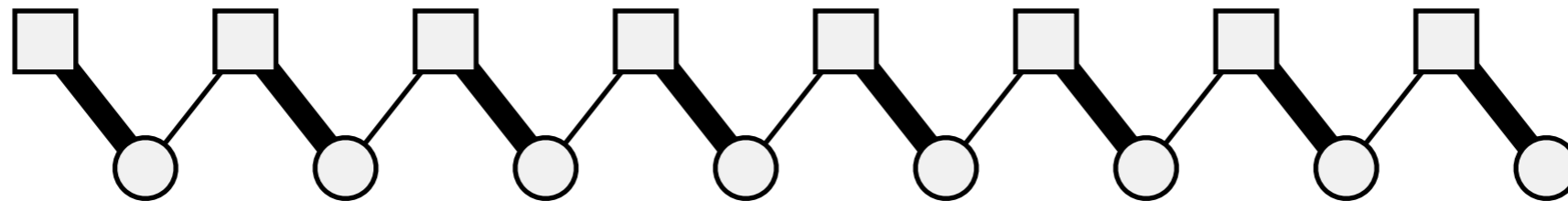
- **Job markets:** open positions and workers
- **Economics:** buyers and sellers
- **Social networks:** marriages
- **Computer networks:** resource allocation

Local Algorithms for Matching in Networks

- **Local perspective:**
 - each player decides with whom to pair based on its local neighbourhood
- **Global perspective:**
 - globally consistent solution, good solution (e.g., large matching)

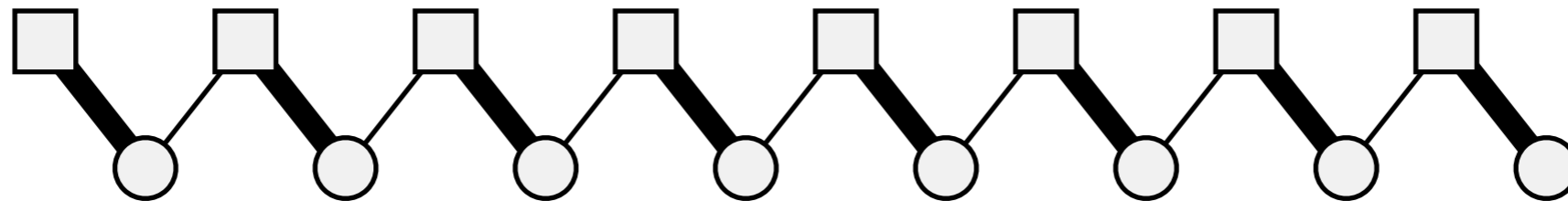
Maximum Matchings

- **Largest possible number of pairs**

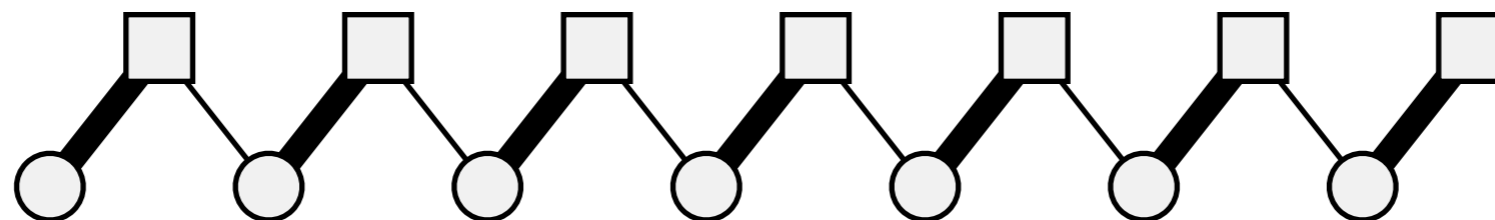


Maximum Matchings

- **No local algorithm – simple proof:**

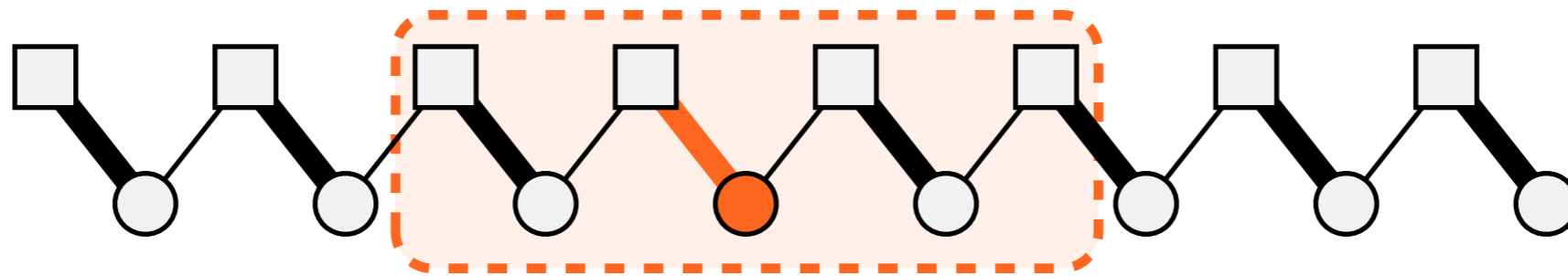


VS.

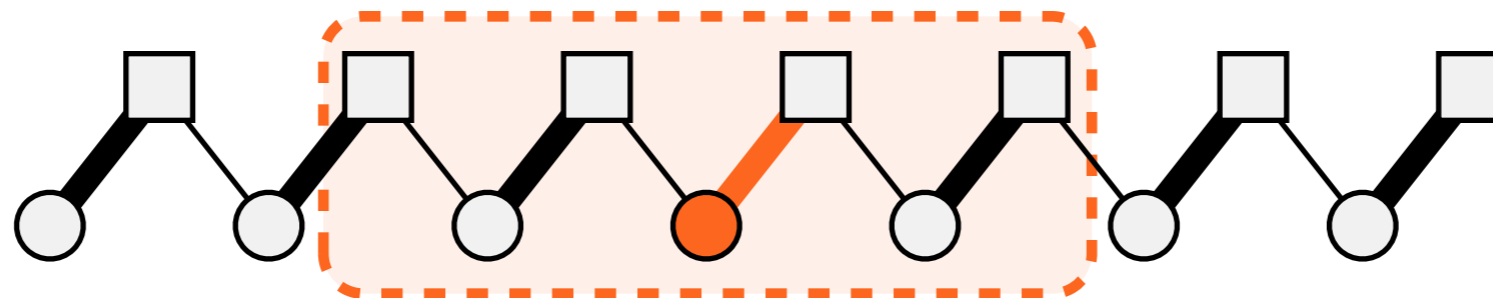


Maximum Matchings

- **Same neighbourhood, different output**



VS.

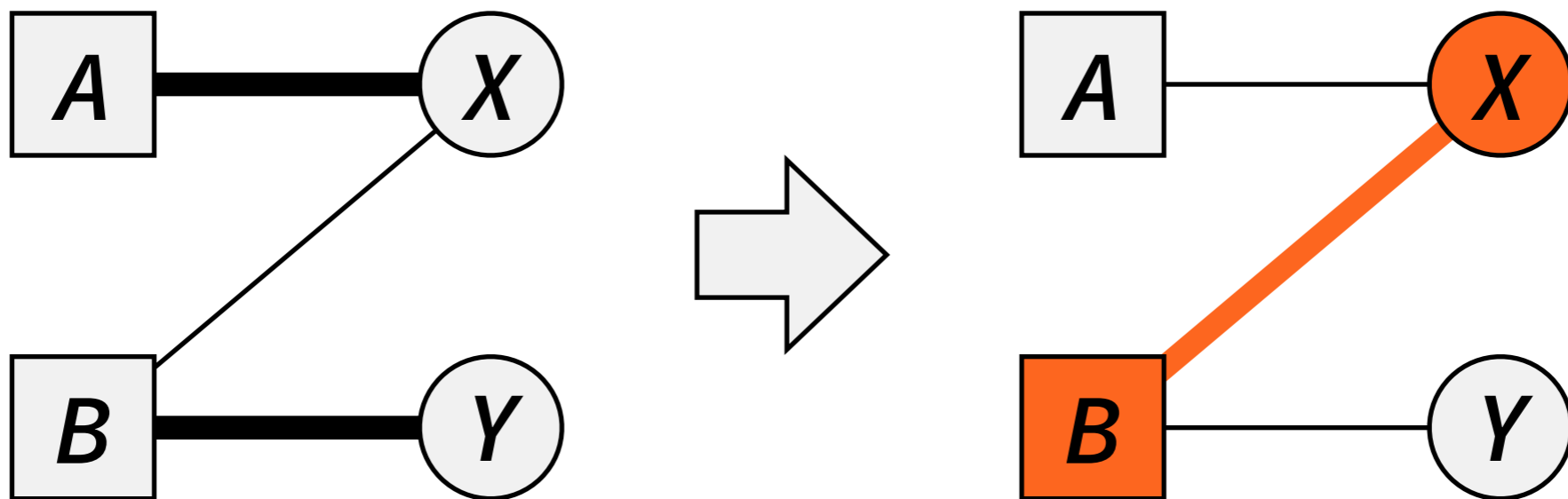


Approximations of Maximum Matchings

- **No local algorithm for maximum matching**
- **However, we can find arbitrarily good **approximations** locally**
 - identify & eliminate all **short** augmenting paths, in parallel
 - local, if maximum degree $O(1)$

Stable Matchings

- No **pair of nodes** has incentive to change
 - X prefers B to A , B prefers X to Y



Stable Matchings

- No **pair of nodes** has incentive to change
- Not possible with local behaviour
 - long path
 - preferences near endpoints determine what we must do near midpoint

Stable Matchings

- No **pair of nodes** has incentive to change
- Not possible with local behaviour
- Possible if we tolerate a **small fraction** of unstable edges
 - simple and natural local algorithm...

Almost Stable Matchings

- **Truncated Gale–Shapley algorithm**
 - currently unmatched “men” propose women in preference order
 - “women” accept the best proposal so far
 - run for $O(1)$ parallel rounds — **local**
- **Few unstable edges** (if low degrees)

Local Algorithms

- **Active subfield of distributed computing**
 - Linial (1992):
“*Locality in distributed graph algorithms*”
 - Naor & Stockmeyer (1995):
“*What can be computed locally*”
 - Kuhn, Moscibroda, Wattenhofer (2004):
“*What cannot be computed locally*”

Local Algorithms for Graph Problems

- **Lots of good approximations — at least in some special cases:**
 - matchings, dominating sets, edge covers, vertex covers, **packing/covering linear programs**, ...
- **More details:** “*Survey of local algorithms*” (2013)

2. Network Science Perspective

- reasons to expect locality
- implications

Why Local?

- **Attractive in computer networks**
 - fast, fault-tolerant, robust
 - cheap and simple
 - easy to design, easy to implement
- **What about social networks, markets, biological systems, industrial systems...?**

Why Expect Locality?

- **Privacy, competition, selfishness**
 - why would strangers reveal what they know?
 - why would our competitors do it?
- **Timeliness**
 - distant information is likely outdated, so why care about it at all?

Why Expect Locality?

- **Simple and unreliable communication**
 - how to encode lots of data in a mixture of some chemical compounds?
- **Simple entities, limited capabilities**
 - could I keep track of friends of friends of friends?

Implications

- **Distributed systems:**
 - **upper-bound results** are of practical use
 - algorithms that we can implement and run
- **Network science:**
 - **lower-bound results** are of practical use?
 - learn about *possible* behaviour in networks

Locality Lower Bounds: Predictions

- **No good matchings in real-world networks**
 - open positions *and* unemployed people
- **No optimal resource allocation**
- **Even if everyone does its best to co-operate!**
 - not price of anarchy but **price of locality**

3. Understanding Locality Lower Bounds

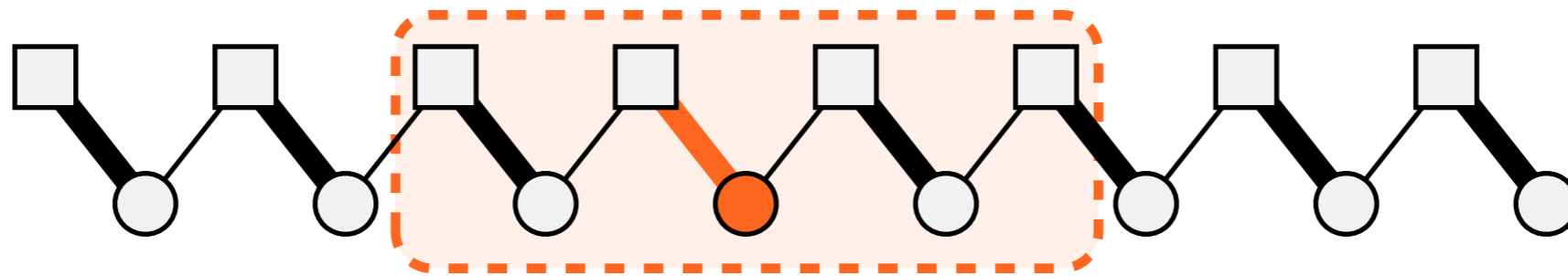
- why are some tasks non-local?

Reasons for Non-Locality

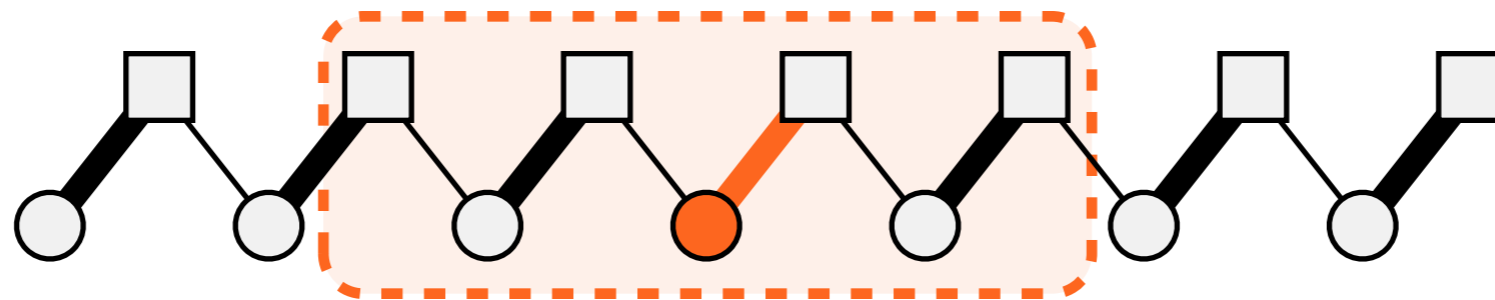
- **Common theme:**
 - nodes u and v have identical local neighbourhoods
 - nodes u and v should make different decisions

Reasons for Non-Locality

- **Example: maximum matching**

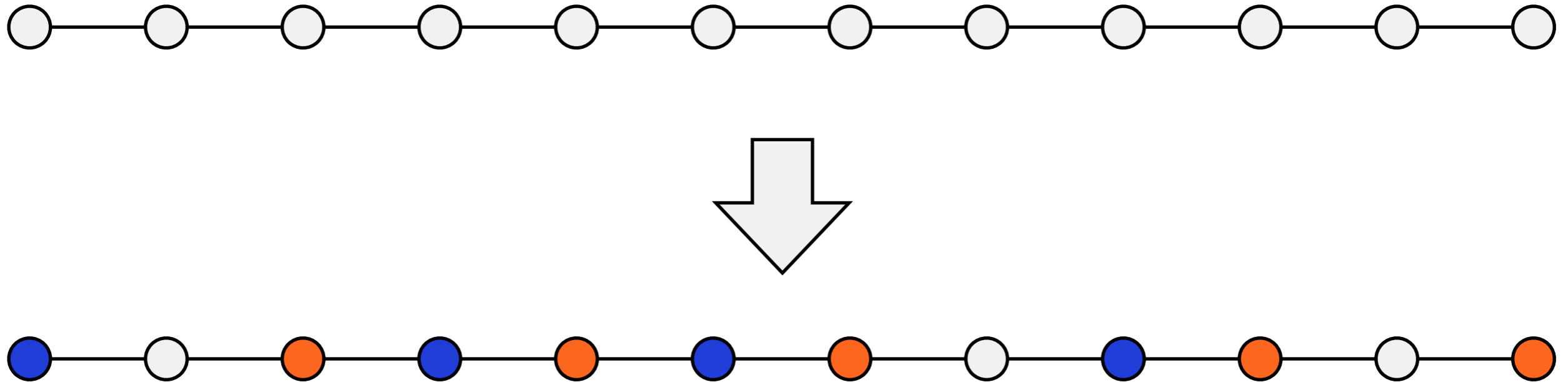


VS.



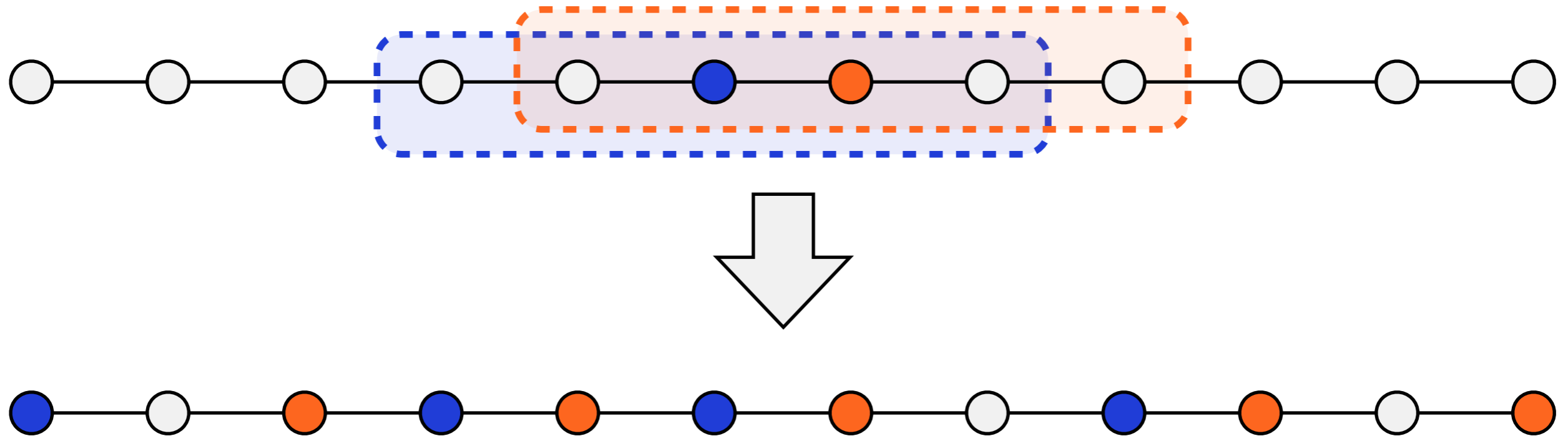
Reasons for Non-Locality

- **Example: graph colouring**



Reasons for Non-Locality

- **Example: graph colouring**

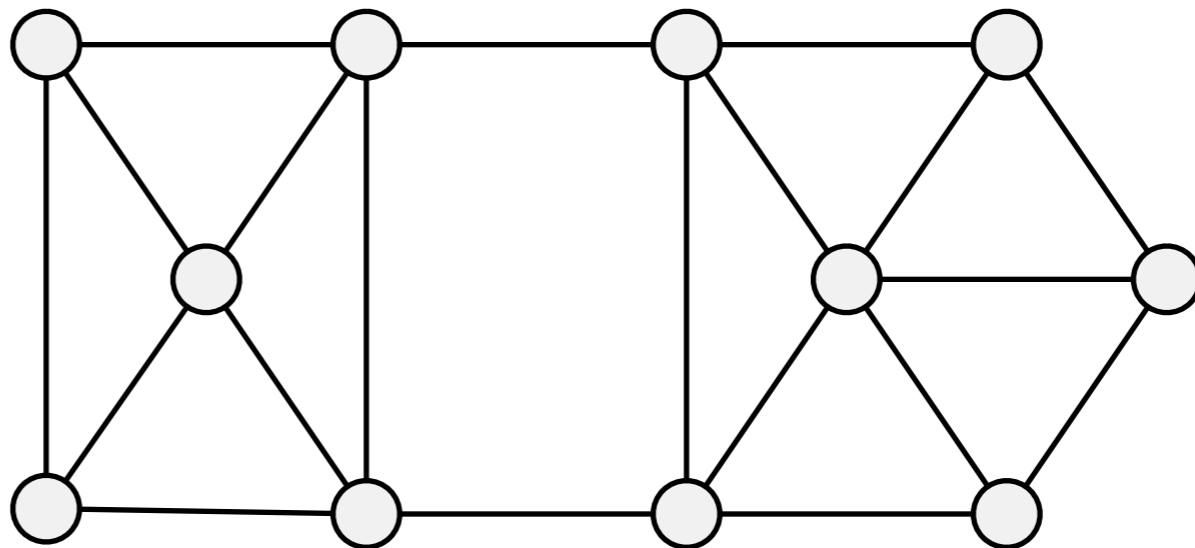


Reasons for Non-Locality

- **Maximum matching:**
 - global optimum needs global information
- **Graph colouring:**
 - extra information needed to break symmetry
- **But there are also less obvious reasons...**

Example: Large Cuts

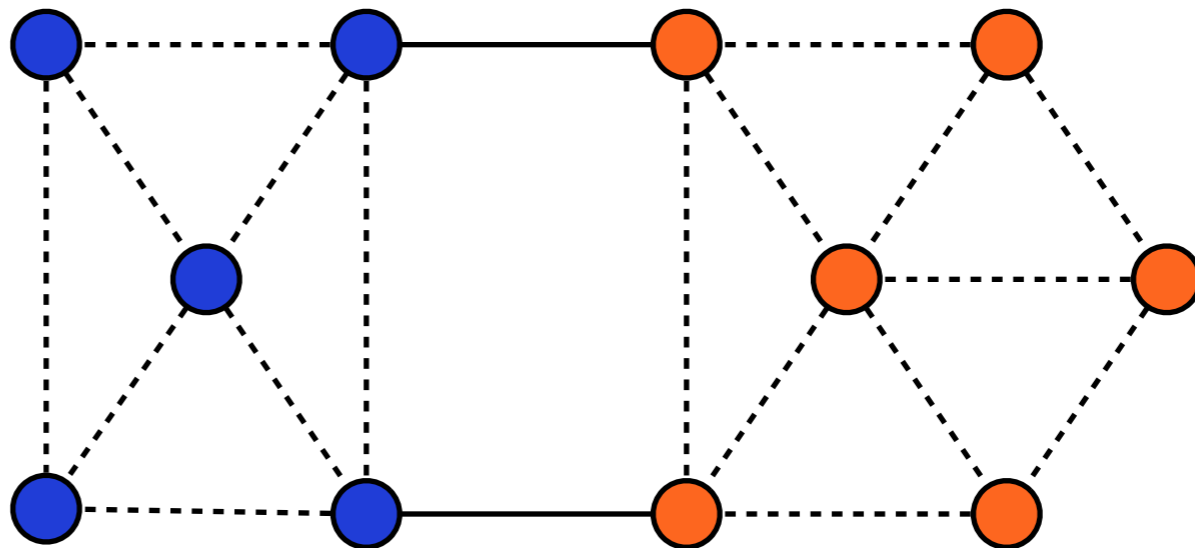
- Label nodes with **orange/blue**
- Cut edge: endpoints with different colours



Example: Large Cuts

- Label nodes with **orange/blue**
- **Cut edge: endpoints with different colours**

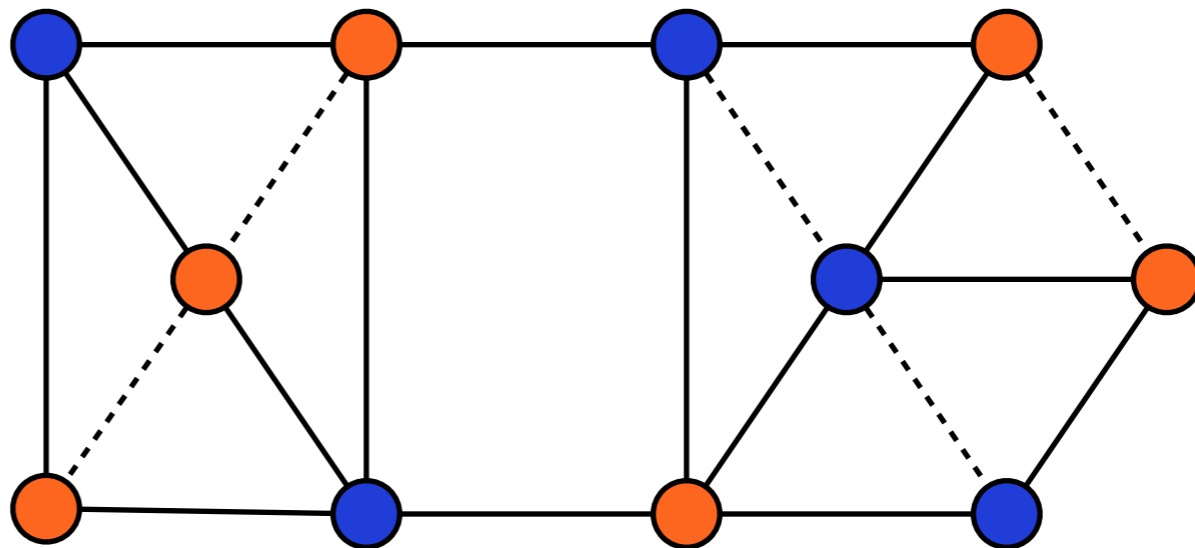
Bad solution:



Example: Large Cuts

- Label nodes with **orange/blue**
- Cut edge: endpoints with different colours

Good solution:

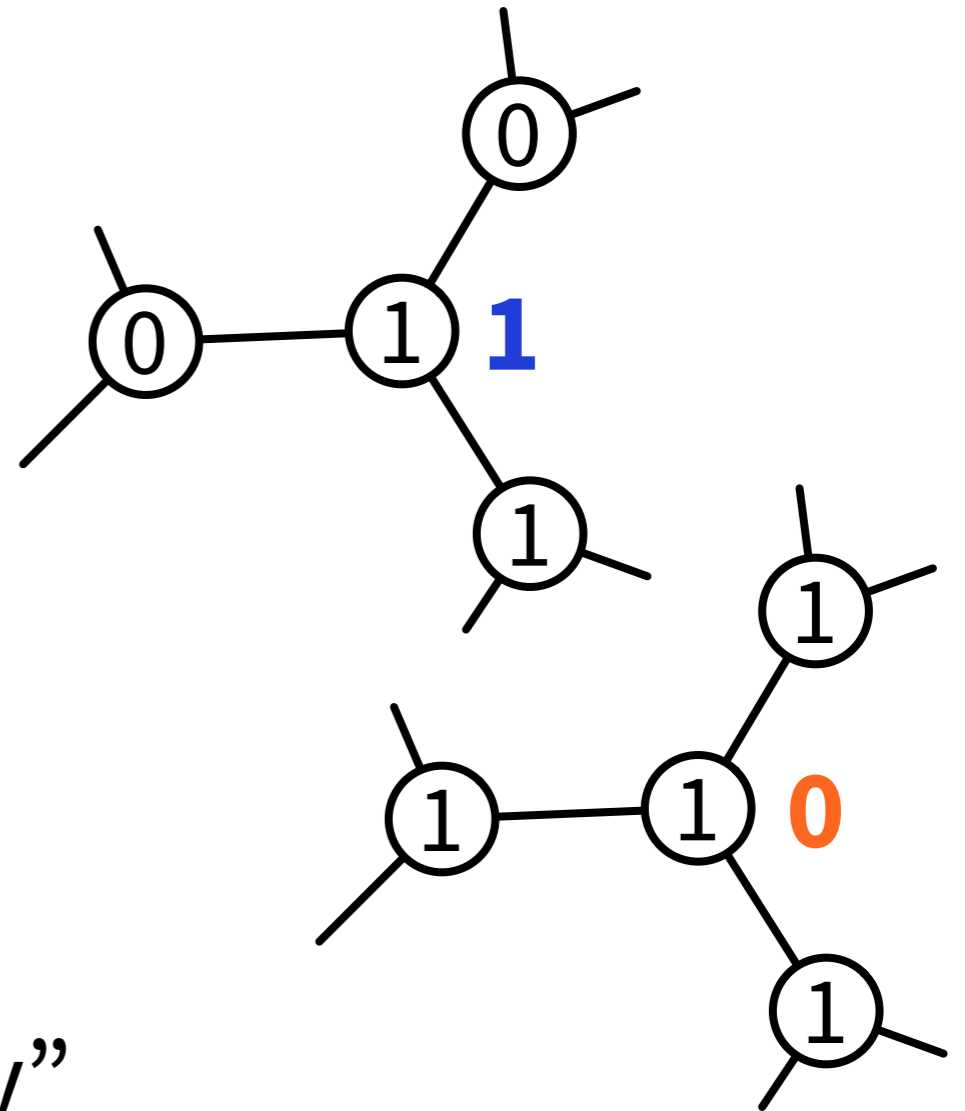


Example:

Large Cuts

- **Simple local rule: flip coins to pick labels**
 - in expectation $1/2$ of all edges are good
 - trivial $1/2$ -approximation
- **Can we do better?**
 - what if we looked further?
 - what if we used more random bits?

Example: Large Cuts



- **We can do *slightly* better:**
 - flip coins
 - **change mind** if “too many” neighbours with the same random bit
 - d -regular triangle-free graphs: $1/2 + \Theta(1/\sqrt{d})$
- **Best possible approximation ratio – why?**

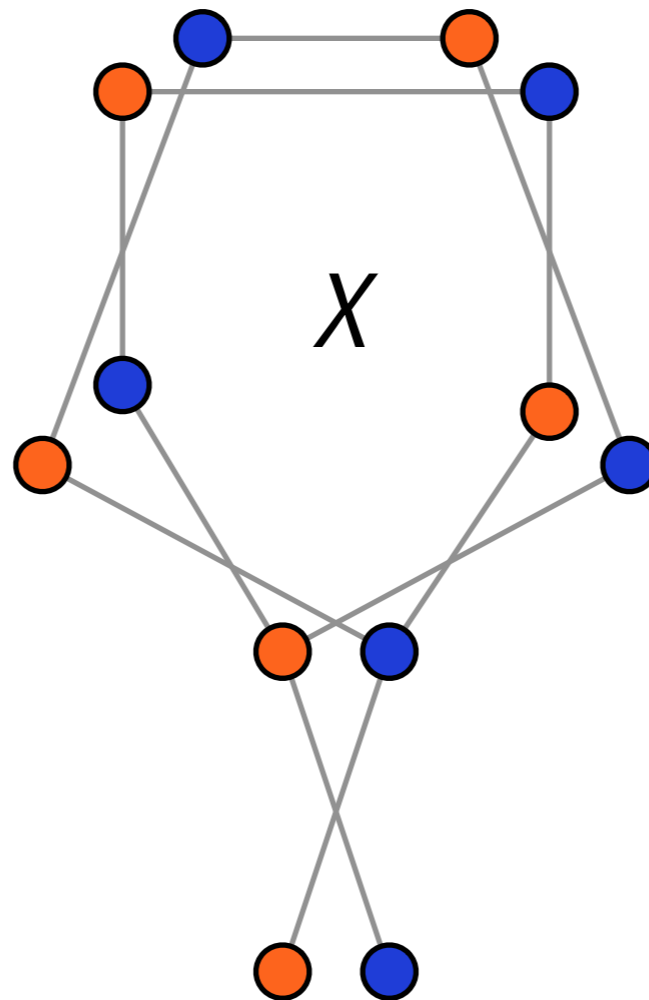
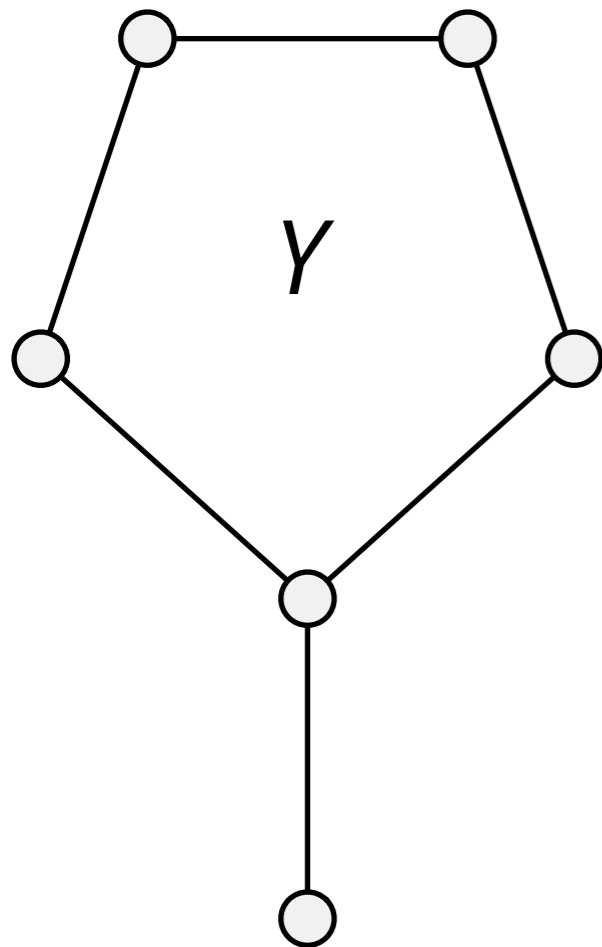
Lower Bound: Large Cuts

- **Networks X and Y look locally identical:**
 - X has large cuts, Y does not have large cuts
- **Local algorithm A : same behaviour in X and Y**
 - must produce small cuts in Y
 - therefore produces small cuts in X , too
 - poor approximation ratio in X

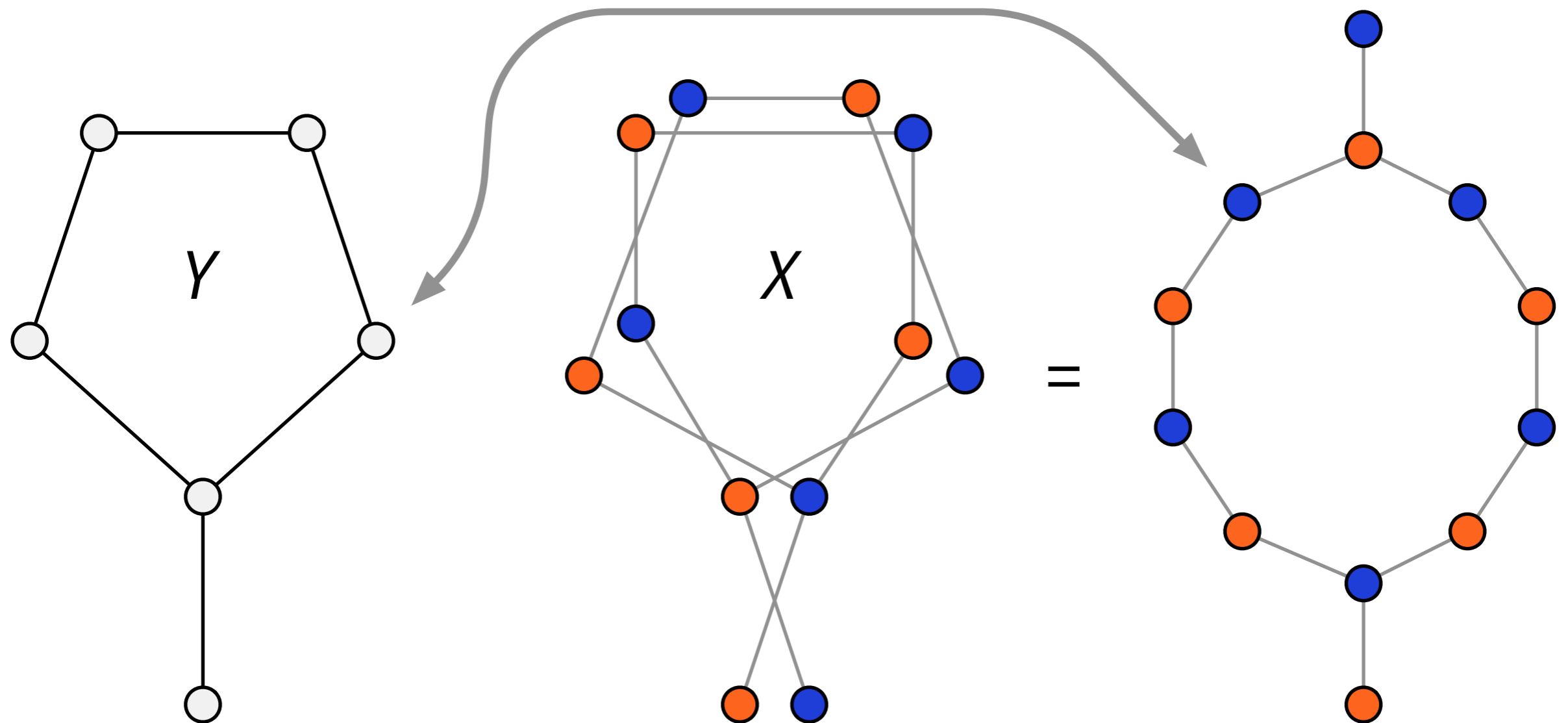
Lower Bound: Large Cuts

- **Y = non-bipartite Ramanujan graphs**
 - high girth — looks locally like a tree
 - no large cuts (**spectral properties**)
- **X = bipartite double cover of Y**
 - looks locally identical to Y
 - has a large cut (**bipartite**)

Bipartite Double Cover



Identical Local Neighbourhoods



Identical Local Neighbourhoods

- **Edge e in Y — similar edges e_1 and e_2 in X**
- **\Pr [edge e_1 in X is a cut edge] =**
 \Pr [edge e_2 in X is a cut edge] =
 \Pr [edge e in Y is a cut edge]
- **E [fraction of cut edges in X] =**
 E [fraction of cut edges in Y]

Reasons for Non-Locality

- **Similar techniques work for many problems**
 - find a **bad counterexample Y**
 - construct an “easy” instance X
 - make sure X and Y look locally identical
 - local algorithm: similar behaviour in X and Y
 - poor approximation in X

Typical Counterexamples

- **Regular graph**
 - node degrees do not help
- **High girth**
 - locally looks like a regular tree
- **Expander graphs**

4. But What About More Realistic Networks?

- do locality lower bounds tell us anything about “typical” networks?

Locality in Real-World Networks

- **Local algorithms for “nice” graph families?**
- **Some progress:**
 - **bounded degrees**
 - bounded growth, bounded independence...
 - bounded arboricity, forbidden minors...
 - line graphs, planar graphs...

Locality in Real-World Networks

- **Distributed computing community focuses on graph families that look like “**typical computer networks**”**
- bounded degrees \approx wired networks
- bounded growth \approx wireless networks

Locality in Real-World Networks

- **Distributed computing community focuses on graph families that look like “**typical computer networks**”**
- **What about job markets, biological networks, social networks, ...?**
 - need to re-think the assumptions

5. Next Steps

- towards tight results in relevant graph families

Research Agenda: Next Steps

- **Radius of locality r vs. parameters of network family**
- **State of the art: r vs. maximum degree Δ**
 - $r = \Theta(1)$ — approximations of max-cut
 - $r = \Theta(\text{polylog } \Delta)$ — approximations of LPs
 - $r = \Theta(\Delta)$ — maximal solutions to LPs

Research Agenda: Next Steps

- **Radius of locality r vs. parameters of network family**
- **Maximum degree:**
 - wrong parameter for social networks
 - tight bounds on r in networks with a small number of high-degree nodes?

Summary:

Locality in Networks

- how to go beyond the traditional scope of ***computer*** networks?