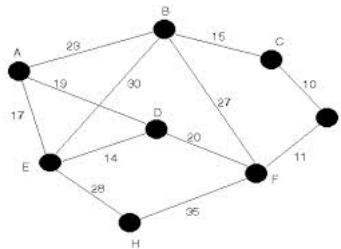


# Graph Algorithms



This is not a pipe.

# Graph Algorithms

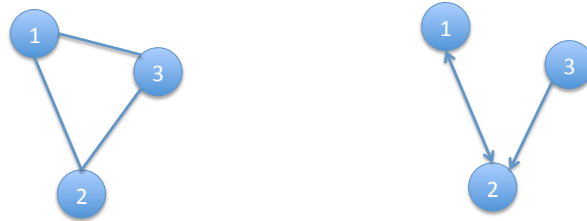


This is not a graph

## Graph Algorithms

- A graph is an ordered set  $(V,E)$ , where  $V$  is a set of vertices and  $E$  is a set of 2 element subsets of  $V$ .
- For example  $V = \{1,2,3\}$ ,  $E = \{\{1,2\},\{3,2\},\{1,3\}\}$
- A directed graph is an ordered set  $(V,A)$ , where  $V$  is a set of vertices and  $A$  is an ordered pair of vertices.
- For example  $V = \{1,2,3\}$ ,  $E = \{(1,2), (2,1), (3,2)\}$

## Graph Algorithms



$V = \{1,2,3\}$ ,  $E = \{\{1,2\},\{3,2\},\{1,3\}\}$

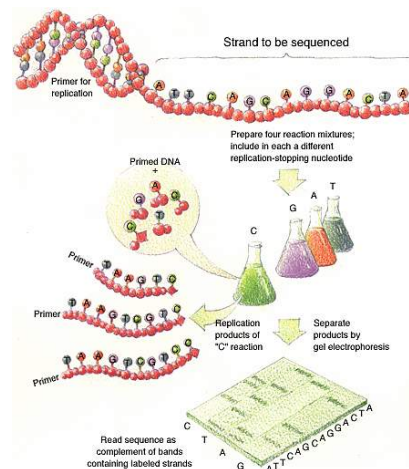
$V = \{1,2,3\}$ ,  $E = \{(1,2), (2,1), (3,2)\}$

## Graph Algorithms

- We will see how some graph algorithms play an important role in genome sequencing.

## DNA Sequencing

- Shear DNA into millions of small fragments
- Read 500 – 700 nucleotides at a time from the small fragments (Sanger method)



## Fragment Assembly

- **Computational Challenge**: assemble individual short fragments (reads) into a single genomic sequence (“superstring”)
- Until late 1990s the shotgun fragment assembly of human genome was viewed as an intractable problem

## Shortest Superstring Problem

- **Problem**: Given a set of strings, find a shortest string that contains all of them
- **Input**: Strings  $s_1, s_2, \dots, s_n$
- **Output**: A string  $s$  that contains all strings  $s_1, s_2, \dots, s_n$  as substrings, such that the length of  $s$  is minimized
- **Complexity**: NP – complete
- **Note**: this formulation does not take into account sequencing errors

## Shortest Superstring Problem: Example

The Shortest Superstring problem

Set of strings: {000, 001, 010, 011, 100, 101, 110, 111}

Concatenation  
Superstring 000 001 010 011 100 101 110 111

Shortest  
superstring

```

      [010]
     [110]
    [011]
   [000]
  0 0 0 1 1 1 0 1 0 0
   [001]
      [111]
       [101]
        [100]
  
```

## Reducing SSP to TSP

- Define *overlap* ( $s_i, s_j$ ) as the length of the longest prefix of  $s_j$  that matches a suffix of  $s_i$ .

aaaggcatcaaatctaaaggcat**aaa**

**aaa**ggcatcaaatctaaaggcatcaaa

What is  $\text{overlap}(s_i, s_j)$  for these strings?

## Reducing SSP to TSP

- Define *overlap* ( $s_i, s_j$ ) as the length of the longest prefix of  $s_j$  that matches a suffix of  $s_i$ .

aaaggcatcaaatctaaaggcatcaaa

aaaggcatcaaatctaaaggcatcaaa

shortest superstring: aaaggcatcaaatctaaaggcatcaaa

## Reducing SSP to TSP

- Construct a graph with  $n$  vertices representing the  $n$  strings  $s_1, s_2, \dots, s_n$ .
- Insert edges of length *overlap* ( $s_i, s_j$ ) between vertices  $s_i$  and  $s_j$ .
- Find the shortest path which visits every vertex exactly once. This is the **Traveling Salesman Problem** (TSP).

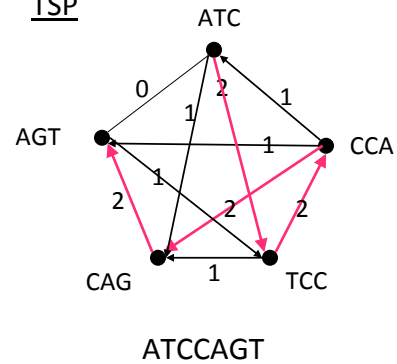
## SSP to TSP: An Example

$S = \{ \text{ATC, CCA, CAG, TCC, AGT} \}$

SSP

AGT  
CCA  
ATC  
**ATCCAGT**  
TCC  
CAG

TSP



What if a problem has:

An exponential upper bound

A polynomial lower bound

The only algorithms that are known to solve the TSP have worst case exponential time complexity. Thus they have an exponential upper bound.

A lower bound for the complexity of a problem is mathematical proof that shows that a certain amount of time is required to solve a problem. The only known lower bounds for the TSP are polynomial.

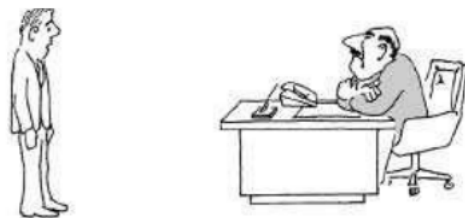
We have only found **exponential** algorithms, so it appears that the problem is “**intractable**”.

But... we can't **prove** that an exponential solution is needed, we can't **prove** that a polynomial algorithm cannot be developed, so we **can't say the problem is intractable...**



Cook, Stephen (1971). "The complexity of theorem proving procedures". Proceedings of the Third Annual ACM Symposium on Theory of Computing. pp. 151–158.

- This paper introduces a concept that handles the conundrum of the mis-match between upper and lower bounds of problems that we strongly believe are hard.



"I can't find an efficient algorithm. I guess I'm just too dumb"



"I can't find an efficient algorithm, because no such algorithm is possible!"



"I can't find an efficient algorithm, but neither can all these famous people."

- What is NP?**

- NP is the set of all decision problems (question with yes-or-no answer) for which the 'yes'-answers can be **verified** in polynomial time ( $O(n^k)$  where  $n$  is the problem size, and  $k$  is a constant)

Polynomial time is sometimes used as the definition of *fast* or *quickly*.

### TSP (Travelling Salesman Problem)

Input: Weighted (directed) graph  $G = (V,E)$ .

Output: A least cost tour that visits every vertex in  $V$  exactly once.

Cannot easily verify that a tour is of least cost. So TSP is not known to be in NP.

DTSP (Decision version of TSP)

Input: Weighted (directed) graph  $G = (V, E)$ ,  
and a number  $K$ .

Output: Is there a tour that visits every  
vertex in  $V$  exactly once of cost  $K$  or less?

Given a tour it's easy to verify whether the  
cost is less than or equal to  $K$ . So we  
just showed that DTSP is in NP.

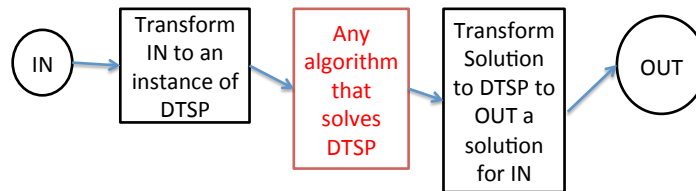
### **What is NP-Complete?**

A problem  $x$  that is in NP is also in NP-  
Complete if and only if every other  
problem in NP can be quickly (ie. in  
polynomial time) transformed into  $x$ . In  
other words:

$x$  is in NP, and every problem in NP is  
reducible to  $x$

if any one of the NP-Complete problems  
was to be solved quickly then all NP  
problems can be solved quickly.

To prove that a problem is NP-complete one needs to provide polynomial transformation algorithms as shown in the black boxes below. IN is an instance of a problem that is known to be NP-complete and OUT the correct YES/NO answer to IN.



Cook showed the first known NP-complete problem (It is known as SAT). Currently there must be thousands of problems that have been shown to be NP-complete.