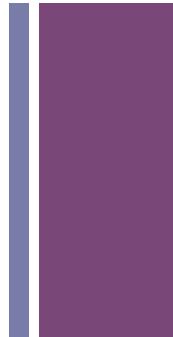


Exact exponential and
fixed parameter algorithms



Map of the next 45 minutes



- By the end of the first hour you will be able to:
 - Define the $O^*(\cdot)$ notation
 - Explain how to solve TSP in $O^*(2^n)$
 - Explain how to solve MIS in $O^*(3^{n/3})$



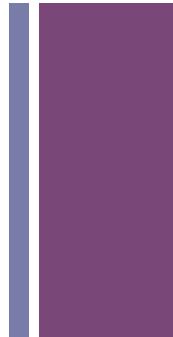
Why bother?

10^6 Instructions per second Input size $n = 10^6$

Time complexity	Running time
n	1 sec.
$n \log n$	20 sec.
n^2	12 days
2^n	40 quadrillion (10^{15}) years



Motivation



- NP-complete problems
- Better understanding of NP-hard problems
- $O(2^n)$ to $O(1.4^n) \rightarrow$ multiplicatively larger instance sizes possible

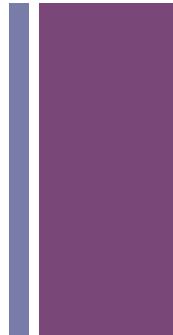
e.g. n^4 vs. $n2^{n/10}$ is worse for $n \leq 100$

Alan Perlis:

“for every polynomial-time algorithm you have, there is an exponential algorithm that I would rather run.”



Exact exponential algorithms



- O^* notation
 - $f = O(g) \rightarrow$ Exist n_0 and c s.t from $n > n_0$, $f(n) < c \cdot g(n)$
 - $f(n) = O^*(g(n)) \rightarrow f(n) = O(g(n)\text{poly}(n))$
- Types of problems:
 - Subset – Maximum independent set
 - Permutation - TSP
 - (Partition – Graph Coloring)

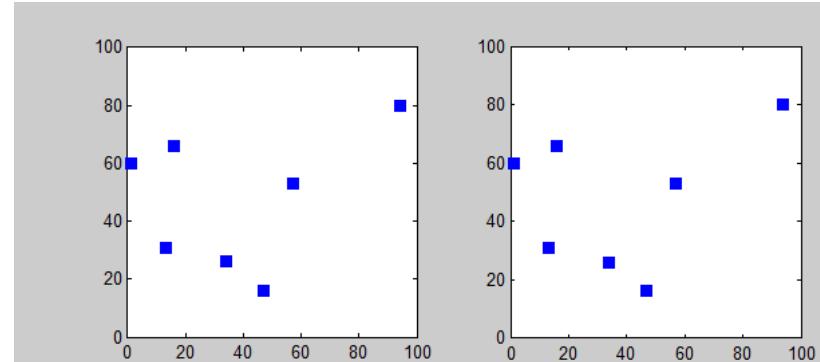


Permutation: TSP

- Given: Cities $\{c_1, c_2 \dots c_n\}$ with distances $d(c_i, c_j)$
- Find the shortest path going through all the cities exactly once and returning to the starting point
- Another point of view: Find the permutation π of $\{1\dots n\}$ that minimizes:

$$\sum_{i=1}^{n-1} d(c_{\pi(i)}, c_{\pi(i+1)}) + d(c_{\pi(n)}, c_{\pi(1)})$$

Naïve solution : $n!$





Improving $O^*(n!)$

- S - subset of $\{c_2 \dots c_n\}$, $c_i \in S$
- Computing for every pair (S, c_i) the optimal tour of S , starting at c_1 and ends at $c_i \rightarrow OPT[S, c_i]$
- $|S| = 1$ is just $d(c_1, c_i)$
- $|S| > 1$

$$OPT[S, c_i] = \min\{OPT[S \setminus \{c_i\}, c_j] + d(c_j, c_i) : c_j \in S \setminus \{c_i\}\}.$$

A smaller group



Adding the distance to c_i

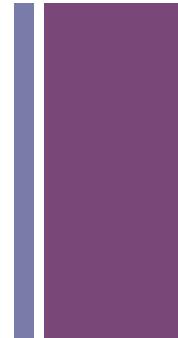


For all elements in the smaller group





Solution explained



Algorithm tsp($\{c_1, c_2, \dots, c_n\}, d$).

Input: Set of cities $\{c_1, c_2, \dots, c_n\}$ and for each pair of cities c_i, c_j the distance $d(c_i, c_j)$.

Output: The minimum length of a tour.

```
for  $i = 2$  to  $n$  do
     $OPT[c_i, c_i] = d(c_1, c_i)$ 
    for  $j = 2$  to  $n - 1$  do
        forall  $S \subseteq \{2, 3, \dots, n\}$  with  $|S| = j$  do
             $OPT[S, c_i] = \min\{OPT[S \setminus \{c_i\}, c_k] + d(c_k, c_i) : c_k \in S \setminus \{c_i\}\}$ 
return  $\min\{OPT[\{c_2, c_3, \dots, c_n\}, c_i] + d(c_i, c_1) : i \in \{2, 3, \dots, n\}\}$ 
```

- The final solution:

$$OPT[\{c_2, \dots, c_n\}, c_i] + d(c_i, c_1) \quad i \in \{1, \dots, n\}$$



Class ex.

For $i=1$ to 3 do

$$f[v_i, s] = d(v_0, v_i)$$

For $j= 1$ to 3 do

for all $S \subseteq \{1,2,3\}$ with $|S| = j$ do

$$f[v_i, s] = \min\{f[S \setminus \{v_i\}, v_k] + d(v_k, v_i) : v_k \text{ from } S \setminus \{v_i\}\}$$

Return $\min\{d(v_i, v_0) + f[v_i, \{v1, v2, v3\}]\} : i \text{ from } \{1,2,3\}$

$$f(1, \phi) = d(1,0) = 1334$$

$$f(2, \phi) = d(2,0) = 1559$$

$$f(3, \phi) = d(3,0) = 809$$

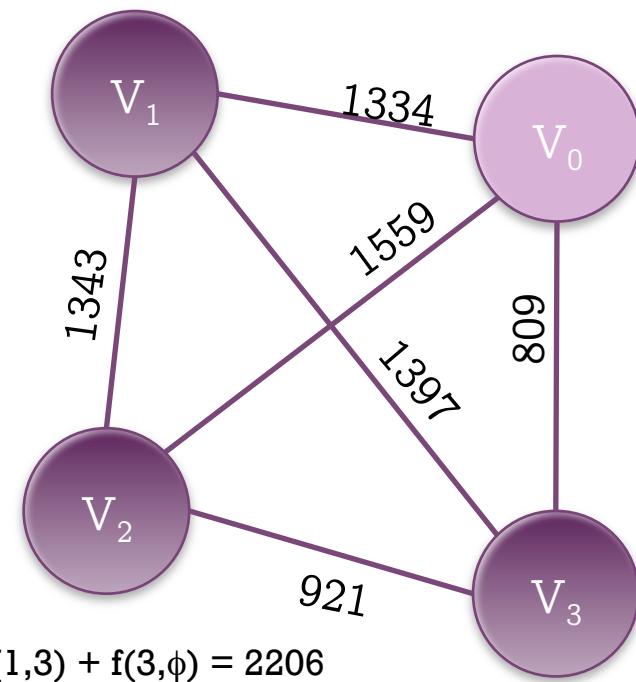
$$f(2,\{1\}) = d(2,1) + f(1,\phi) = 2677$$

$$f(3,\{1\}) = d(3,1) + f(1,\phi) = 2731$$

$$f(1,\{2\}) = d(1,2) + f(2,\phi) = 2902$$

$$f(3,\{2\}) = d(3,2) + f(2,\phi) = 2480$$

$$f(1,\{3\}) = d(1,3) + f(3,\phi) = 2206$$



+

$$|S| = 2$$

```

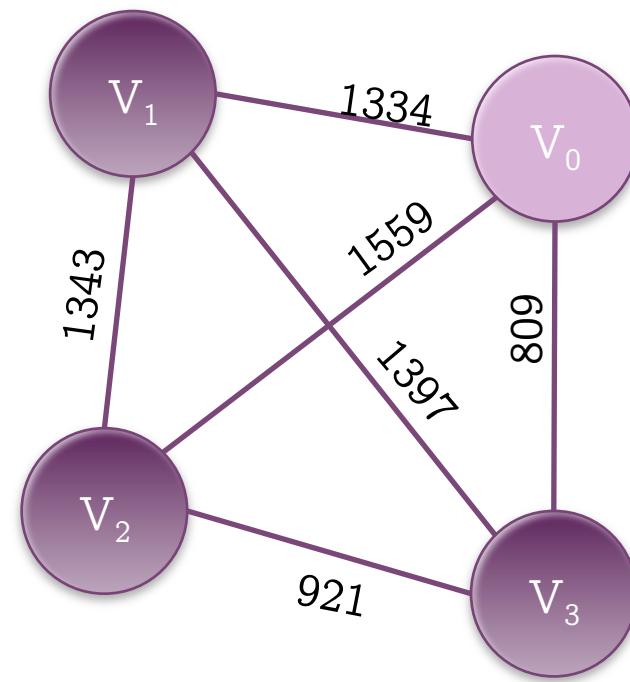
For i=1 to 3 do
    f[vi,s] = d(c0,ci)
For j= 1 to 3 do
    for all S ⊆ {1,2,3} with |S| = j do
        f[vi, s] = min{F[S \ {vi], vk] + d(vk, vi): vk from S \ {vi}}
Return min{d(vi, v0) + f[vi, {v1,v2,v3}]: i from {1,2,3}}

```

- Possible values for s: {1,2}, {1,3}, {2,3}

$$f(3,\{1,2\}) = ? ; \quad f(2,\{1,3\}) = ? ; \quad f(1,\{2,3\}) = ?$$

$$\begin{aligned}
f(3,\{1,2\}) &= \min \{d(3,j) + f(j,s \setminus \{j\}): j \text{ in } \{1,2\}\} \\
&= \min \{d(3,1) + f(1,\{2\}), d(3,2) + f(2,\{1\})\} \\
&= \min \{1397+2902, 921+2677\} \\
&= \min \{4299, 3598\} \\
&= 3598, \quad N(3,\{1,2\})=\{2\}
\end{aligned}$$



+

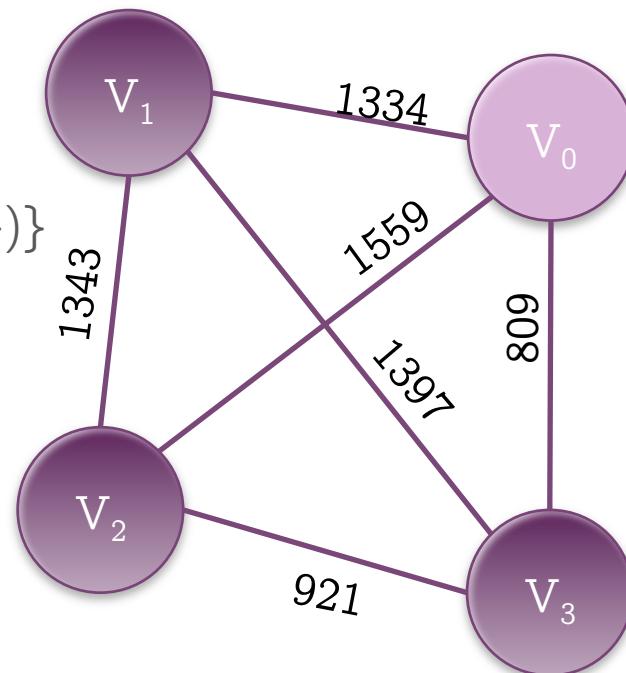
$$|S| = 3$$

```

For i=1 to 3 do
    f[vi,s] = d(c0,ci)
For j= 1 to 3 do
    for all S ⊆ {1,2,3} with |S| = j do
        f[vi, s] = min{F[S \ {vi}, vk] + d(vk, vi): vk from S \ {vi}}
Return min{d(vi, v0) + f[vi, {v1,v2,v3}]: i from {1,2,3}}

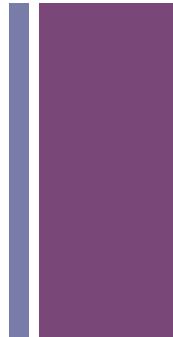
```

$$\begin{aligned}
f(0, \{1,2,3\}) &= \min \{d(0,j) + f(j, \{1,2,3\} \setminus \{j\}): j \text{ in } \{1,2,3\}\} = \\
&\min \{d(0,1)+f(1,\{2,3\}), d(0,2)+f(2,\{1,3\}), d(0,3)+f(3,\{1,2\})\} \\
&= \min \{1334+3073, 1559+3549, 809 + 3598\} \\
&= \min \{4407, 5108, 4407\} = 4407, N(0, \{1,2,3\}) = \{1,3\}
\end{aligned}$$





Complexity



- $\text{OPT}[S, c_i] = \min\{\text{OPT}[S \setminus \{c_i\}, c_j] + d(c_j, c_i) : c_j \in S \setminus \{c_i\}\}.$

$|S| = k$, each step is $O(k^2)$

Why?

-Choosing c_i (k possible), and for each finding the preceding best c_j .

How many subsets are there?

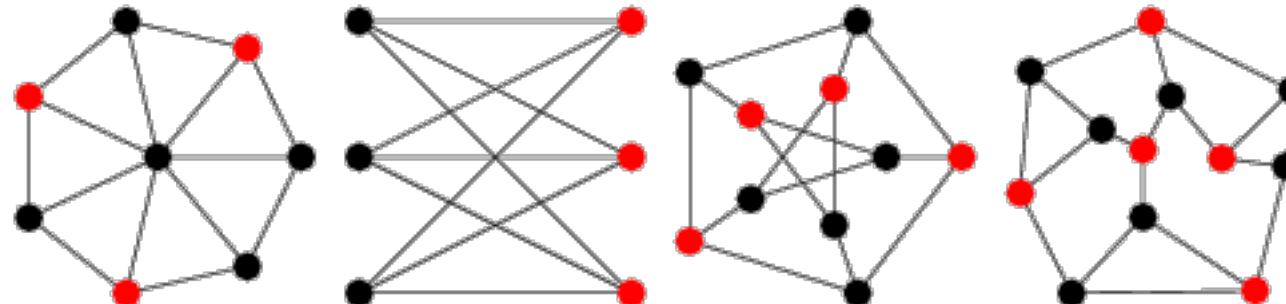
For given k - $\binom{n}{k}$, Over all k 's $\sum_{k=1}^{n-1} \binom{n}{k}$

Together: $\sum_{k=1}^{n-1} \binom{n}{k} k^2 = O*(2^n)$



Subset: Maximum Independent Set

- Given: undirected graph $G=(V,E)$
- Find the largest subset of $I \subseteq V$ s.t any pair of vertices in I is non-adjacent
- Naïve solution: try all 2^n possible subsets





Improving $O^*(2^n)$

- If v is in I , none of its neighbors are in I .
- If v is not in I , at least one of its neighbors is, but then none of its neighbors are in I .

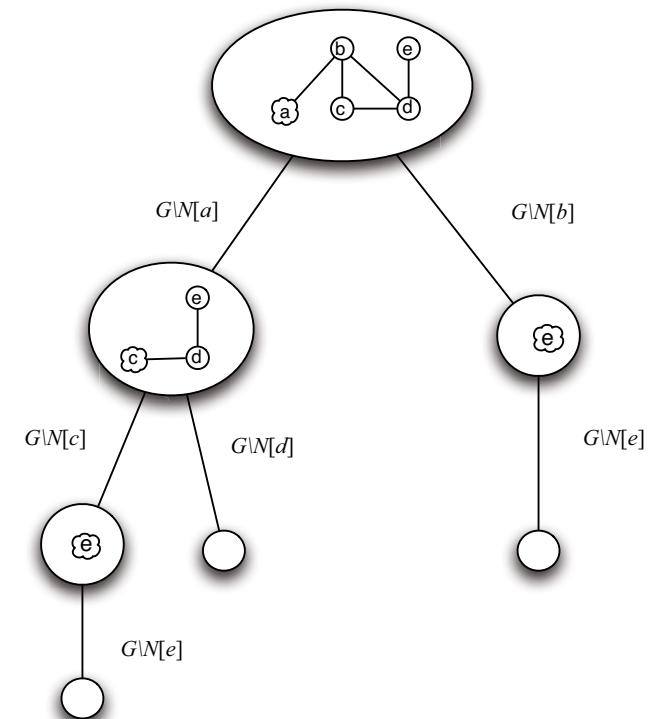
Algorithm mis1(G).

Input: Graph $G = (V, E)$.

Output: The maximum cardinality of an independent set of G .

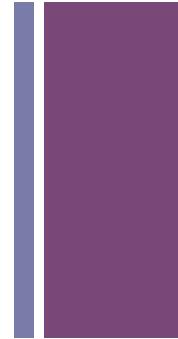
```
if  $|V| = 0$  then
    ↳ return 0
```

```
choose a vertex  $v$  of minimum degree in  $G$ 
return  $1 + \max\{\text{mis1}(G \setminus N[y]) : y \in N[v]\}$ 
```





Recursion tree



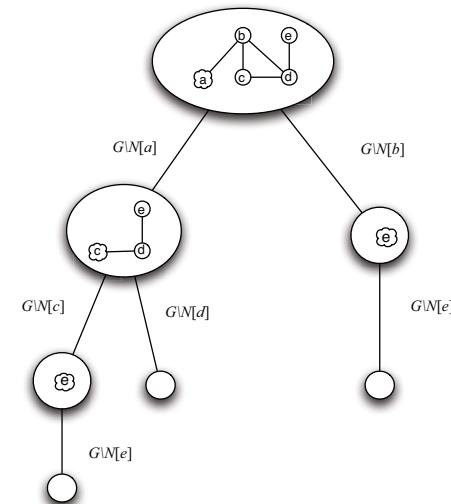
For a node v with $d(v)$ children

If v is in, none of his neighbors are

$$T(n) \leq 1 + T(n - d(v) - 1) + \sum_{i=1}^{d(v)} T(n - d(v_i) - 1).$$

The solution with each of the rest.
 $d(v_i)$ the degree of the selected node.
 $1 \leq i \leq d(v)$

We chose the a node with minimal degree,
so $d(v) \leq d(v_i)$



+

Complexity analysis - 1

$$T(n) \leq 1 + T(n - d(v) - 1) + \sum_{i=1}^{d(v)} T(n - d(v_i) - 1).$$

$$d(v) \leq d(v_i) \rightarrow n - d(v_i) - 1 \leq n - d(v) - 1$$

T is a monotonically increasing $\rightarrow T(n - d(v_i) - 1) \leq T(n - d(v) - 1)$

$$T(n) \leq 1 + T(n - d(v) - 1) + \sum_{i=1}^{d(v)} T(n - d(v) - 1)$$

In other words,

$$T(n) \leq 1 + (d(v) + 1) \cdot T(n - d(v) - 1).$$



Finally...

$$T(n) \leq 1 + (d(v) + 1) \cdot T(n - d(v) - 1).$$



We assign $s = d(v) + 1$ and get:

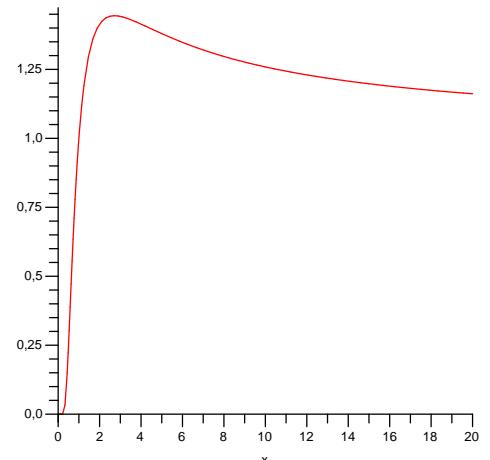
$$T(n) \leq 1 + s \cdot T(n - s) \leq 1 + s + s^2 + \dots + s^{n/s}$$

Geometric series bounded $O^*(S^{n/s})$

Written differently: $s^{n/s} = (s^{1/s})^n$

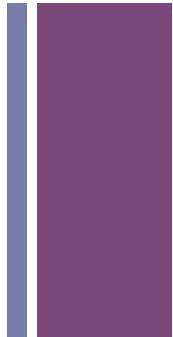
The function $s^{1/s}$ peaks at $s=3$, thus:

$$T(n) = O^*(3^{n/3})$$





Part 2- FPT



- By the end of this section you will be able to:
 - Define what is an FPT algorithm
 - Explain how to get a k^2 kernel for vertex cover
 - Explain how to get a k^2 kernel for max-satisfiability
 - Understand what is kernelization and what is its connection with FPT



The "classical" P vs. NP framework
is one-dimensional

$n = \text{input size}$

$\text{poly}(n)$

vs

$2^{\text{poly}(n)}$

"good"

P

positive toolkit of how to
design P-time algorithms

"bad"

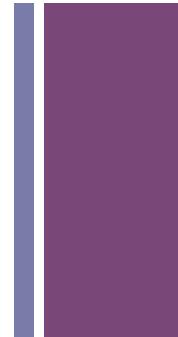
NP, etc.

negative toolkit of
NP-hardness, etc.

Unfortunately, almost everything turns out to be NP-hard.



The parameterized framework is two-dimensional



n = input size

k = a relevant secondary measure

$f(k)n^c$

vs

$n^{g(k)}$

“good”

“bad”

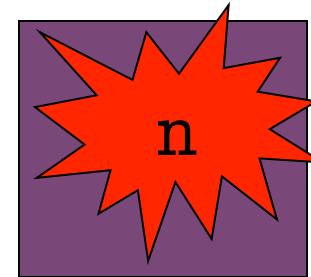
FPT

Not discussed in this lecture

+ Framework in pictures

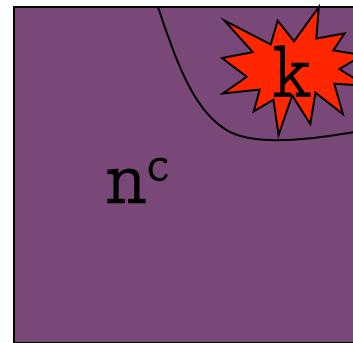
The *classical* P vs NP framework

Intrinsic Combinatorial explosion: Most problems are NP-hard or worse.



The *parameterized* framework

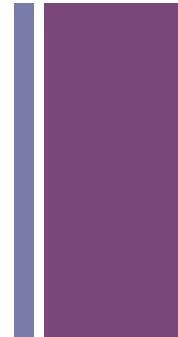
FPT



Try to confine the explosion to the parameter.



Vertex cover

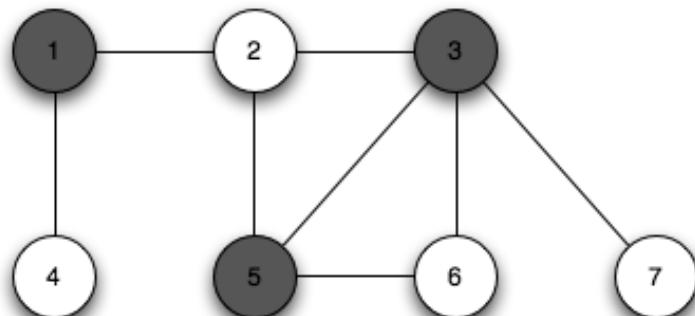


- An NP-complete problem
- Easily parameterized (by the size of the set)

Vertex-cover(G, k)

Input: An undirected graph $G = (V, E)$ and a nonnegative integer k .

Task: Find a subset of vertices $C \subseteq V$ with k or fewer vertices such that each edge in E has at least one of its endpoints in C .

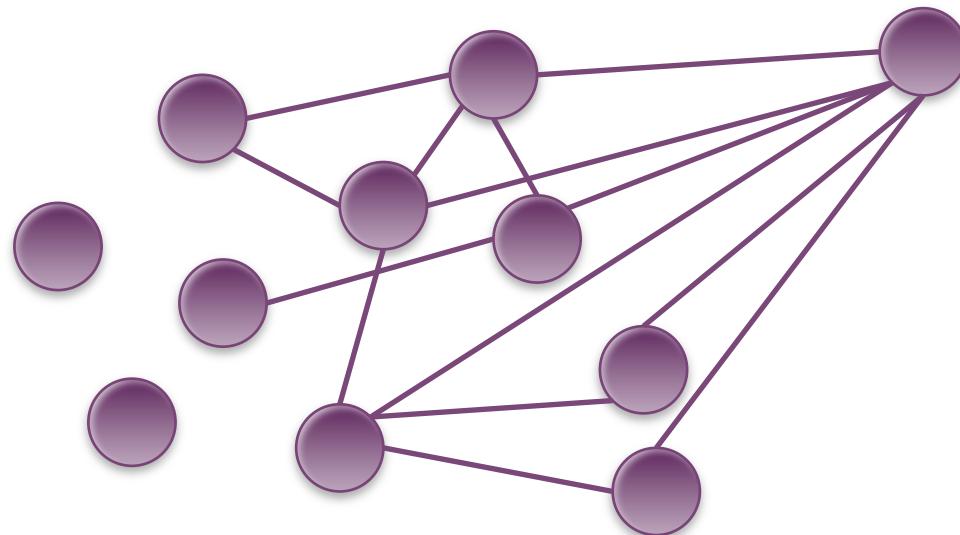


Any other parameters?



Vertex cover: Observations

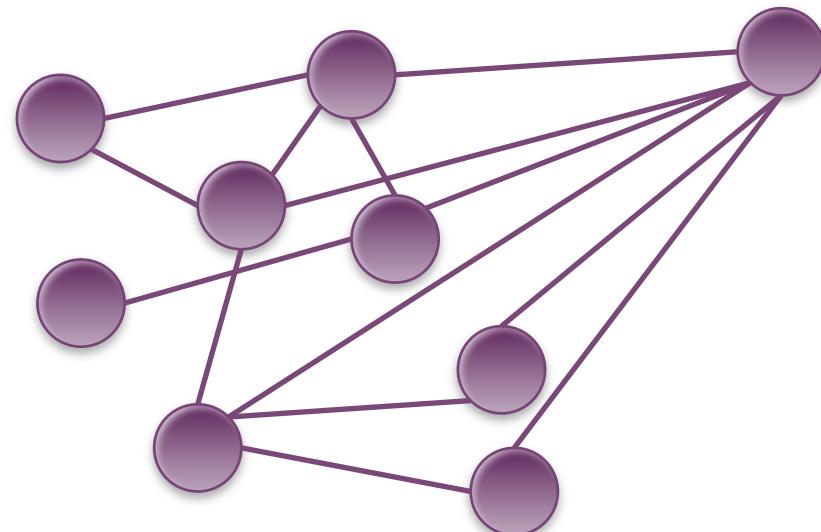
- First, all vertices without edges connected are discarded.





Vertex cover: Observation 1

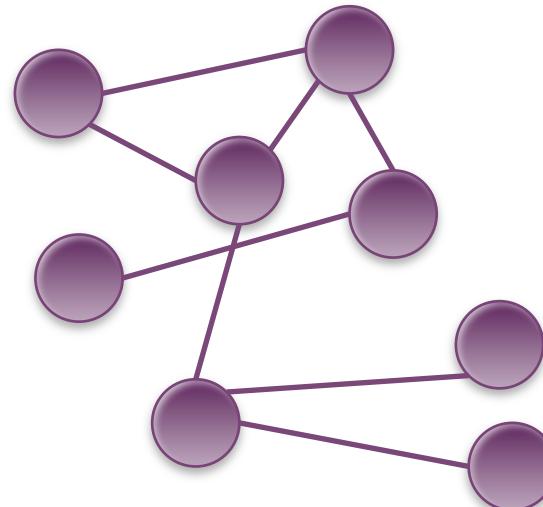
- If v has degree at least $k+1$, then v belongs to each vertex cover in G of size at most k .
- If v is not in the vertex cover, then all its neighbors are in the vertex cover.





Vertex cover: Observation 2

- (After applying observation 1) We are left with vertices with degree at most k
- Every edge needs to be covered, but every vertex has at most k neighbors.
 - Thus, if we have more than k^2 edges, no Vertex cover is possible





We are left with

- At most k^2 edges and at most $2k^2$ vertices are left (otherwise we can safely reject the instance)

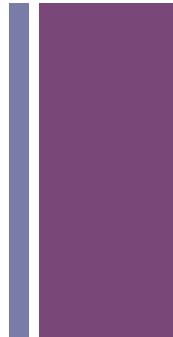
Iterating on the vertices in the kernel we can achieve a running time of :

$$O^*(2^{2k^2})$$

- Exponential explosion ? Yes, but only w.r.t k and not n.



Definitions



- A *parameterized* problem is a language

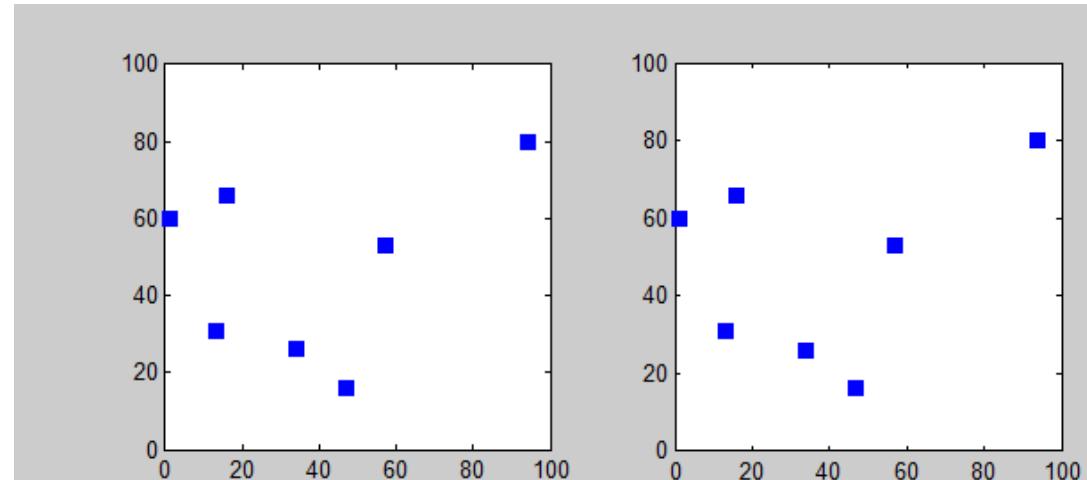
$L \subseteq \Sigma^* \times \Sigma^*$, where Σ is a finite alphabet. The second component is called the *parameter* of the problem.

- A parameterized problem is *fixed-parameter tractable* if it can be determined in $f(k) \cdot |x|^{O(1)}$ time whether $(x, k) \in L$, where f is a computable function only depending on k . The corresponding complexity class is called *FPT*.



TSP is also FPT ...

- for $k = \text{number of cities}$ by “try all permutations” implies a $- k! n$ algorithm
- A parameterized problem can be “trivially FPT”
- As before, “better FPT” $2^k n$ is desirable





Kernelization

- Reduce starting instance to $f(k)$ size instance, in polynomial time
- Use any algorithm to solve problem on kernel
- Total time:

$$p(n) + g(f(k))$$





Formal definition of kernelization

- Let L be a parameterized problem, that is, L consists of (I, k) , where I is the problem instance and k is the parameter.
- *Reduction to a problem kernel:* replace instance (I, k) by a “reduced” instance (I', k') (called *problem kernel*) such that:
 1. $k' \leq k$, $|I'| \leq g(k)$ for some function g only depending on k
 2. $(I, k) \in L$ iff $(I', k') \in L$
 3. The reduction from (I, k) to (I', k') has to be computable in polynomial time.



Kernelization for Vertex Cover

$H = G; (S = \emptyset ;)$

While there is a vertex v in H of degree at least

$k+1$ do:

 Remove v and its incident edges from H

$k = k - 1; (S = S + v ;)$

If $k < 0$ then return false

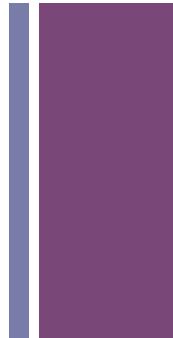
If H has at least k^2+1 edges, then return false

Remove vertices of degree 0

Solve vertex cover on (H,k) with some algorithm



CNF, a reminder

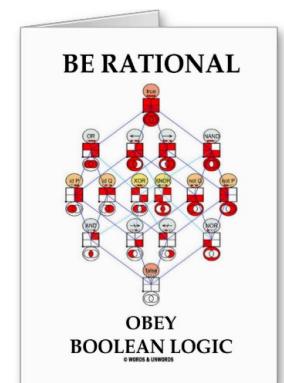


- A formula is in conjunctive normal form (CNF) if it is a conjunction of clauses, where a clause is a disjunction of literals
- Example :

$$(x_1 \vee x_2 \vee \neg x_3) \wedge (x_1 \vee x_2 \vee x_3) \wedge (\neg x_1 \vee x_2 \vee x_3) \wedge (x_2)$$

The size of the instance is the number of literals in total

In this example : 10





MAXIMUM SATISFIABILITY

- Input: A boolean formula F in conjunctive normal form consisting of m clauses and a nonnegative integer k .
- Task: Find a truth assignment satisfying at least k clauses.

$$(x_1 \vee \neg x_2 \vee x_3) \wedge (x_1 \vee x_2 \vee x_3) \wedge (x_1 \vee x_2 \vee x_3) \wedge (x_2)$$

Kernel of size k^2



Observation 1:

- If $k \leq \lceil m/2 \rceil$, then the desired truth assignment trivially exists:
 - Take a random truth assignment.
 - If it satisfies at least k clauses then we are done.
 - Otherwise, flip the assignment

$$(x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_1 \vee x_2 \vee x_3) \wedge (x_1) \wedge (x_1 \vee \neg x_2)$$

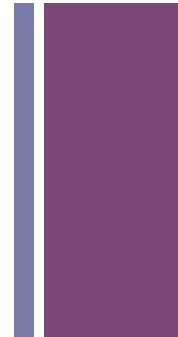
Class ex.:

1. Find an assignment that satisfies at most 2 clauses
2. Show that by flipping the assignment, 3 or more clauses are satisfied

We can assume $k > \lceil m/2 \rceil \rightarrow m < 2k$



Flipping : Class ex.



$$(x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_1 \vee x_2 \vee x_3) \wedge (x_1) \wedge (x_1 \vee \neg x_2)$$

$$x_1=F \quad x_2=T \quad x_3=F$$

1,4,5 are false 2 and 3 are true. Let's flip it!

$$x_1=T \quad x_2=F \quad x_3=T$$

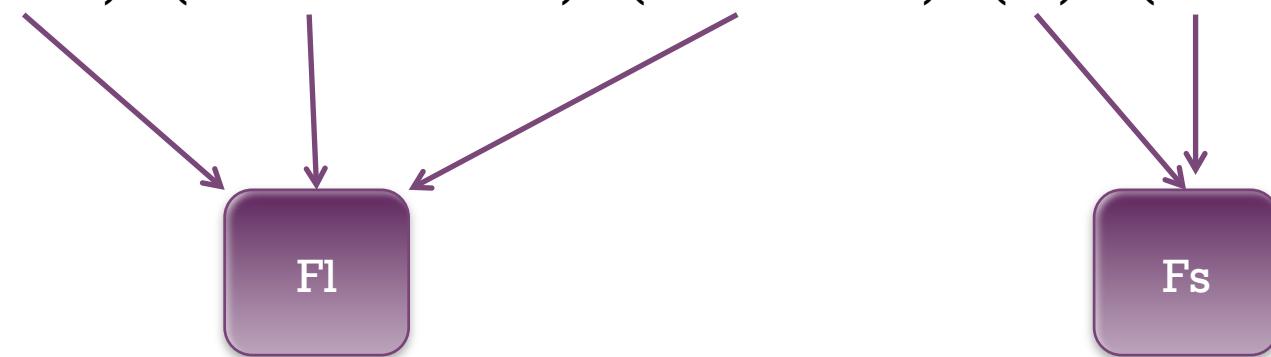
Without even looking at 2 or 3, we know that 1,4,5 are now satisfied



Observation 2:

- Partition the clauses of F into F_l and F_s :
 F_l : long clauses containing at least k literals;
 F_s : short clauses containing less than k literals.

$$(x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_1 \vee x_2 \vee x_3) \wedge (x_2) \wedge (x_1 \vee \neg x_2)$$





Observation 2 (cont.)

- Let $L := \text{number of long clauses } (|F_l|)$.
- If $L \geq k$, then at least k clauses can be satisfied.
 - for each (w.c) pick one literal and set it to satisfy the formula $(x_1 \vee \neg x_2 \vee x_3 \vee \dots \vee x_k \vee \dots \vee x_{c_i})$

F_l

F_s

Now we are left with the case where $L < k$



Example

- $(x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_1 \vee x_2 \vee x_3) \wedge (x_2) \wedge (x_1 \vee \neg x_2)$
- The 3 members of F_1 are the first 3.
- We can set x_1 as the first clause demands (T), x_2 for the second (F) and x_3 for the third (T)
- We are now secure that at least k (3) clauses are satisfied



Observation 3:

- By now we already know that the instance has $L < k$ large clauses and the total number of clauses m is strictly smaller than $2k$
- (F, k) is a yes-instance if and only if $(Fs, k - L)$ is a yes-instance.



Observation 3:

- (F, k) is a yes-instance if and only if $(Fs, k - L)$ is a yes-instance.

->if (F, K) has an assignment, there are between 0 and L large clauses satisfied but certainly no less than $k-L$ small clauses.

Thus, if there is an assignment for (F, k) there must also be one for $(Fs, k - L)$



Observation 3:

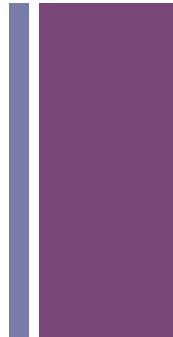
- (F, k) is a yes-instance if and only if $(Fs, k - L)$ is a yes-instance.

<- if $(Fs, k - L)$ is a yes-instance of MaxSat:

1. To satisfy $k - L$ clauses at most $k - L$ variables (at most one variable per satisfied clause) are needed to be assigned, leaving L variables unassigned.
2. we can use the trick before and satisfy all the large clauses and get (F, k) of MaxSat

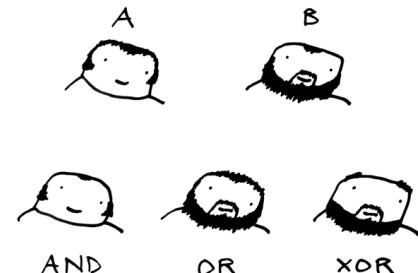


Conclusion



- $|F_s| = O(k^2)$ because :
 - There are $m - L \leq m$ small clauses, each containing at most k literals
 - $m < 2k$
 - The total number of literal occurrences in F_s is bounded from above by $2k \cdot k = 2k^2$.
- MAXIMUM SATISFIABILITY has a problem kernel of size $O(k^2)$

BOOLEAN HAIR LOGIC





Recall: Formal definition of Kernel

- Let L be a parameterized problem, that is, L consists of (I, k) , where I is the problem instance and k is the parameter.
- *Reduction to a problem kernel:* replace instance (I, k) by a “reduced” instance (I', k') (called *problem kernel*) such that:
 1. $k' \leq k$, $|I'| \leq g(k)$ for some function g only depending on k
 2. $(I, k) \in L$ iff $(I', k') \in L$
 3. The reduction from (I, k) to (I', k') has to be computable in polynomial time.



The connection: Kernels and FPT

- **Theorem:** Consider a decidable parameterized problem. Then the problem belongs to FPT, if and only if it has a kernel

<= Build the kernel and then solve the problem on the kernel

=> A little trickier ...



FPT -> Kernel

→ assume that the given fixed-parameter algorithm has running time $f(k) \cdot n^c$.

- Run this algorithm on the problem for at most n^{c+1} steps
- two cases are possible:
 1. The algorithm has finished its task within that time, now we have a kernelization algorithm running in polynomial time n^{c+1} , which simply outputs either a trivial “no”-instance or a trivial “yes”-instance.
 2. The algorithm is not finished, but we can argue that $n < f(k)$. Thus, our problem kernel is the original input instance itself.



Tips and tricks for selecting the parameter

- Parameter really small
 - Example: Vertex Cover on planar graphs
- Guaranteed parameter value
 - Example: Independent set on planar graphs
- More than one obvious parameterization
 - Example :Weighted vertex cover
- Close to trivial problem instances
 - Example :Traveling Salesperson problem in the two-dimensional Euclidean plane