

Advanced Algorithms Theory Swiss Knife



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# Graph – General Definitions

* as the graph itself
  + = set of vertices (aka nodes)
  + (cartesian product = all) is a collection of edges
    - an edge is a pair of vertices
      * it indicates the connection between two nodes
      * a connection of vertices allows for repetition
* directed graphs, which happens if
* undirected graphs, which happens if
* arc = edge inside directed graphs (also called *directed edges*)
* given an edge
  + is incident on and (happens if vertex if one of endpoints in that edge)
  + and are adjacent (there is an edge between the two vertices)
* neighbors of a vertex: all vertices s.t.
  + all vertices directly connected to a given vertex by an edge
* degree of a vertex , denoted as or
  + the number of edges incident on
* path: and
  + finite/infinite sequence of nodes which joins a sequence of vertices via edges
* simple path: (all vertices) are all distinct
  + same definition as above and vertices/nodes are all distinct/so are the edges
  + e.g., has repeated twice so it’s not simple
* cycle: simple path s.t. (starts from a given vertex/ends at same node)
* subgraph:
  + the edges of are incident only on vertices of
  + in words: it is a subset of the larger original graph
* spanning subgraph: a subgraph with
  + a subgraph which “spans” the original graph (so there are all the vertices)
  + following other definitions
    - subgraph obtained by edge deletions only but retaining all vertices
    - so it’s a subgraph of with same vertex set as
* connected graph: if a path from to
* connected components: a partition of in subgraphs
  + is connected
  + there is no edge between and
* tree: connected graph without cycles
  + any two vertices are connected by *exactly* one path
* forest: set of trees (disjoint)
  + also = undirected graph in which any two vertices are connected by *at most* one path
* spanning tree: a spanning subgraph connected and without cycles
* spanning forest: a spanning subgraph without cycles

Generally, remember:

* (number of nodes)
* (number of edges)
* the size of a graph is

There are also multiple ways of representing:

* an adjacency list
  + an array of lists, one vertex (consider the example below)
  + each containing all the vertices adjacent to (represented by table below)

|  |  |
| --- | --- |
| 1 | 2,5 |
| 2 | 1,3,4,5 |
| 3 | 2,4 |
| 4 | 2,5,3 |
| 5 | 4,1,2 |

Immagine che contiene cerchio, linea, diagramma, schizzo

Descrizione generata automaticamente

What if directed? Only vertices pointed for that vertex.

* Pro: space usage i.e. linear
* Con: no quick way to determine if a given edge is in the graph
* an adjacency matrix
  + a matrix s.t. if , otherwise



Immagine che contiene schermata, numero, Carattere, diagramma

Descrizione generata automaticamente



* If graph is directed 🡪 the matrix is *asymmetric*
* If graph is undirected 🡪 the matrix is *symmetric*

In case of a *weighted graph*, each cell of the matrix has either the value of the edge weight (as number) or to represent null costs. This kind of graph represents costs, capacities, etc.

* Pro: Quick to determine if a given edge is present
* Con: Space required is 🡪 can be superlinear in the input size
  + if number of vertices increases, the space required by matrix grows quadratically

# Depth First Search - DFS

## Description

The algorithm starts at the root node (selecting some arbitrary node as the root node in the case of a graph) and explores as far as possible along each branch before backtracking. It may find:

* new edges (discovery edge)
* non-tree edges, linked to ancestors (back edges)

Visit a vertex, then a neighbor of the vertex, then a neighbor of the neighbor – these are all neighbours, classified with adjacency lists.

## Algorithm

## Complexity

Given:

* : number of vertices of (one invocation )
* : number of edges of (costs related to node, excluding recursive invocations inside)

The complexity overall is:

More in general: – vertices and edges

## Applications

There are several:

* path (between two generic vertices)
  + done adding a field
* finding cycles
  + use field on vertices and on edges
* find connected components
  + run the algorithm times
  + consider all untouched vertices
  + see which have back edges, meaning they “close” the cycle
  + otherwise, return
* find a spanning tree

# Breadth First Search - BFS

## Description

The algorithm is iterative, starts from a source vertex and visits all vertices connected to a specific component, partitioning them in levels according to their distance. It still has discovery edges:

* but adds cross edges – which connect vertices at different levels

## Algorithm

## Complexity

## Applications

* Same as for DFS in time

So, again:

* path (between two generic vertices)
  + done adding a field
* finding cycles
  + use field on vertices and on edges
* find connected components
  + run the algorithm times
  + consider all untouched vertices
  + see which have back edges, meaning they “close” the cycle
  + otherwise, return
* find a spanning tree

# Minimum Spanning Tree – MST

* Input: a graph undirected, connected and *weighted*
  + A weight
  + defines cost of edge
* Output: a spanning tree of s.t. is minimized
  + Goal is minimizing the sum for all weights of every edge of the tree

## Generic Greedy Algorithm

## Definitions

* A cutof graph is a partition of
  + in words, a partition of vertices into two disjoint subsets
  + it can be done on one or more edges
* An edge crosses a cut if and (or viceversa)
  + so, if its endpoints lie in different subsets of the partition defined by the cut
* A cut respects a set of edges if no edge of *crosses* the cut
* Given a cut, an edge that crosses the cut and is of minimum weight is called light edge(for that cut) 🡪 they are useful, because when included in MSTs, they have minimum weight

There is also the *minimum cut*, for which we have , where is a generic size of graph. Summing up all vertices, we obtain , concluding it’s .

# Prim’s Algorithm

## Description

The algorithm is iterative and selects light edges at every step, growing a spanning tree from there. Consider this [gif](https://en.wikipedia.org/wiki/Prim%27s_algorithm#/media/File:PrimAlgDemo.gif) to see the running. We have to preserve “safe edge” property – take only minimal edges not already inside of the tree.

## Algorithm

## Complexity

## Example of Execution for Exam

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Descrizione generata automaticamente

Traversal:

# Efficient Prim – Heap Implementation

## Description

The previous is not so efficient in large structures. The right kind of data structure to improve the algorithm is a *priority queue*, implemented with a heap.

* Recap about this data structure
  + 🡪 add an object to the heap (possibly fast)
  + 🡪 remove an object with the smallest key (highest priority)
  + 🡪 given a pointer to an object, remove it
* In a heap with objects, the complexity of these operations is

We can redefine the algorithm exploiting this efficient data structure basically with the same principle:

* consider a min heap starting from whatever vertex, which is the root
* from there, always extract the minimum value (means checking if it is min heap),
  + then update the path

## Algorithm

## Complexity

* 🡪
* 🡪 iterations
* 🡪

Total cost of only operations:

* *for loop*: executed times in total (every vertex is explored)
  + - this here is a simple check
    - two operations

Total cost of *for loop*: (iterating for all adjacent nodes, quantity equal to node degree)

This way, the total complexity of the algorithm is (since is connected, we recall) 🡪 near-linear time.

# Kruskal’s Algorithm

## Description

It picks the minimum weighted edge at first and the maximum weighted edge at last. It sorts edges by weight and then adds them continuously, preserving the “safe edge” property – take only the unexplored. It does so preventing the adding of cycles.

## Algorithm

## Complexity

* sorting:
* for loop: check whether closes a cycle is equivalent to check whether contains an path 🡪 DFS on 🡪 complexity:

Total: 🡪

## Example of Execution for Exam

Immagine che contiene disegno, clipart, schizzo, Line art

Descrizione generata automaticamente

Traversal:

# Efficient Kruskal – Union-Find

## Description

It can be implemented as fast as Prim’s, considering the most frequent operation here is cycle check (equivalently, path check), which happens when an edge is added to .

We create a new data structure supporting this operation fast and to do that, we use a structure called Union-Find (also called *disjoint set*). This is a structure to merge *disjoint sets* (also non-overlapping in their elements) of objects and supports at least three operations:

* *Init*: given an array of objects
  + it creates a Union-Find data structure with each object in its own set
* *Find*: given an object , return the name of the set that contains
  + depth: number of edges traversed by *Find*
* *Union*: given two objects merge the sets that contain and into a single set
  + done whenever the sets are distinct
  + if are already in the same set, this operation does nothing

## Algorithm

## Complexity

* Init:
* Sorting:
* Find:
* Union: 🡪 only when I go inside an “if” and when the edge is added
* updating:

In total:

# Shortest Path

* Given a weighted graph, the length of a path is defined as
* A shortest path from a vertex to a vertex is a path with minimum length among all paths
* The distance between vertices and , denoted as is the length of a shortest path from to ; if there is no path at all from to then

The problem itself is the following:

* Given a directed, weighted graph and a source vertex and a destination , compute the shortest path from to

# Single-Source Shortest Path (SSSP)

* input: a directed, weighted graph with edge weights and a source vertex
* output:
  + shortest path to all destinations

There are two major cases to solve: a special one and a more general one.

# Non-negative weights – Dijkstra

## Description

Dijkstra's algorithm finds the shortest path from one vertex to all other vertices. It does so by repeatedly selecting the nearest unvisited vertex and calculating the distance to all the unvisited neighboring vertices.

* input: directed ,
* output:
  + with coming as shorthand form of the previous one

## Algorithm

## Complexity

# Efficient Dijkstra – Heap

## Description

Normal implementation uses adjacency list. This implementation improves efficiency by using a priority queue (usually implemented as a binary heap) to select the vertex with the smallest tentative distance efficiently. The implementation is almost identical to Prim with heaps.

## Algorithm

(almost identical to Prim’s implementation with heaps)

## Complexity

* considering graph as adjacency list, vertices and edges
* iterations because of heap usage

Total number of operations: (there are operations on heaps)

# General Case: SSSP Problem

We reformulate the previous problem a bit:

* Input: a directed weighted graph and a source vertex
* Output: one of the following
  + vertex
  + a declaration that contains a negative cycle

Need to forbid negative cycles in shortest paths, they lead to infinitely small paths, which is an NP-Hard problem.

The main Dijkstra problems are two:

* It never revisits/updates its decisions, but it should for all vertices!
  + Once a vertex is marked as “closed”, we will never develop this node again
  + If we have a vertex in open such that its cost is minimal - by adding any positive number to any vertex - the minimality will never change
  + Without the constraint on positive numbers - the above assumption is not true
  + It assumes them to be positive to make the algorithm run faster and does this to avoid considering paths which can’t be shorter
* should be an *estimated distance*, which needs to be updated for every vertex
  + how many times? edges times should be enough
  + maximum number of edges in a simple path between any two vertices

# Bellman-Ford’s Algorithm

## Description

* Input: A directed graph with edge weights and a source vertex
* Output: Either or a declaration that contains a negative cycle

The algorithms is used when the graph might possess negative weights and can even detect negative cycles. If the graph contains one, there is no cheapest path, instead one can make it cheaper by one more walk around said negative cycle (in iterations it reaches a fix-point, if it doesn’t it means a negative cycle exists). Still, it’s slower compared to Dijkstra.

## Algorithm

## Complexity

# All-Pairs Shortest Paths (APSP)

* Input: A directed, weighted graph
* Output: One of the following:
  + ordered vertex pair
  + a declaration that contains a negative cycle
    - this can be problematic in finding a shortest path
    - now we would have to output shortest paths

Consider:

* If we use Bellman-Ford - very high complexity 🡪
  + Using dynamic programming, the complexity can be reduced to
  + This holds rewriting B-F recurrence controlling the allowable size of the input

# Floyd-Warshall’s Algorithm

## Description

It’s used to find the shortest paths between all pairs of nodes in a weighted graph, with positive or negative edges.

* instead of restricting the number of edges allowed in a solution, restrict the identities of the vertices that are allowed in a solution
  + in other words, now paths can pass through only certain vertices
* Basically, it compares many possible paths through the graph between each pair of vertices

It iterates on vertices: i n 3 nested loops, testing whether using 𝑘 in the path is better.

## Algorithm

## Complexity

# Maximum Flows

* a flow network is a directed graph where each edge has a capacity , along with a designated source and sink
  + for convenience, write if , no edges enter and no edges leave
* a flow is a function satisfying the following constraints (how much stuff I send through the edges in general)
  + (*capacity*) – value of the flow at most capacity of that edge
  + (*conservation*) we have
  + the amount of flow going in nodes must be equal to the flow going out from those (conservation of flows)
    - initially, such flow is 0, which is “how much we can pass on the edge”
* the value of a flow is
  + basically, the sum of all flows going in and out vertices thanks to edges
  + as a matter of fact, the amount of stuff traveling from source to sink
  + such flow has to be less than or equal to the capacity

As for the problem itself:

* given a flow network, find a flow of maximum value. Such flow is measured on *the maximum value received in a sink node*

# Ford-Fulkerson’s Algorithm

## Description

Given a flow network a flow , the residual network of w.r.t (with respect to) flow , , is a network with vertex set and with edge set as follows:

* for every edge in
  + if , add to with capacity
  + if , add another edge to with capacity

The Ford-Fulkerson (F-F) algorithm repeatedly finds an path in (e.g., using BFS) and uses to increase the current flow.

* is called augmenting path
  + This is a path of edges in the residual graph with unused capacity greater than from the source to the sink
  + This can only flow on edges not fully saturated yet
* In an augmenting path, the *bottleneck* is the smallest edge on the path. We can use this one to augment the flow along the path

Immagine che contiene cerchio, schermata, linea, diagramma

Descrizione generata automaticamenteIn figure below, in orange the augmenting path, in light-blue as written the bottleneck:

* Augmenting the flow means updating the flow values along the augmenting path (left)
  + For forward edges, this means increasing the flow by the bottleneck value
* When augmenting the flow along the augmenting path
  + you also need to decrease the flow along each residual edge (backward edges) by the bottleneck value (right)
  + Immagine che contiene schermata, cerchio, linea, diagramma

    Descrizione generata automaticamenteresidual edges exist to “undo” bad augmenting paths which do not lead to a maximum flow

Immagine che contiene schermata, cerchio, linea, diagramma

Descrizione generata automaticamente

The residual graph, so, contains also residual edges. This algorithm continues to find augmenting paths and augments the flow until no more augmenting paths exist.

* The algorithm simply takes in every iteration the bottleneck
* Then considers the bottleneck and keeps incrementing selecting every possible path until max flow is reached
* Each iteration is then reported into the residual graph, accounting for the bottleneck
  + e.g. if we chose in an iteration, in the next iteration
    - forward (remaining)
    - backward (spent)

## Algorithm

## Complexity

* Assume capacities are integers; then
  + the flow value increases by is each iteration
  + the complexity of each iteration is

Total complexity is , where is a max flow

# NP-Hardness

There are problems which can be solved in linear time:

* e.g. Eulerian circuit – a graph where edges are traversed all at once

There are problems which can be solved in polynomial time:

* e.g. Minimum Spanning Tree (MST), minimizing the weights inside all tree

There are also problems where no polynomial algorithms are present to solve the problem:

* e.g. Traveling Salesperson Problem (TSP), Hamiltonian Circuit

We define the following *complexity classes*:

1. is the set of decision problems that can be solved in polynomial time
2. is the set of decision problems with the following property:
   1. if the answer is YES, then there is a proof of this fact (called “certificate”) that can be checked in polynomial time
3. , which is essentially the opposite of :
   1. property: if the answer is NO, then there is a proof of this fact that can be checked in polynomial time

Other features of problems:

* a problem is said to be NP-Hard if a polynomial time algorithm for this one would imply the existence of a polynomial time algorithm for every problem in NP
* More formally, a problem is NP-Hard if every problem in NP reduces in polynomial time to it
  1. unless , which is not yet solved
  2. if a problem is NP-Hard, it provides evidence the problem may not be in
* a problem is NP-Complete if it’s both in NP and NP-Hard
  1. e.g. the Cook-Levin Theorem for Boolean Satisfiability problem (SAT)
     1. made up of clauses with conjunction/disjunction, usually 3 (3-SAT)

We use a reduction given it’s a very powerful tool:

* a reduction is an algorithm for transforming one problem into one another
* a problem reduces to if there is an algorithm able to solve can be translated into one which solves
* remember reductions works from (problem I know to be hard) to (new problem)
* Immagine che contiene testo, disegno, calligrafia, diagramma

  Descrizione generata automaticamentethe reduction is FROM
  1. I already know it’s NP-hard
* to
  1. the “new” problem

## NP-Hard Problems

* Independent Set
  1. given a graph an independent set in is a subset with no edges between them
* (Maximum) Independent Set (this one will be referred to as simply “Independent Set” meaning the latter)
  1. compute an independent set of maximum size
* SAT/3-SAT (thanks to Cook-Levin Theorem)
  1. SAT - Boolean satisfiability of a formula (has to be equal to TRUE)
  2. 3-SAT - Boolean satisfiability of a formula made by 3-clauses
* Hamiltonian Circuit
  1. a cycle that traverses all the vertices only once
* (Maximum) Clique
  1. largest complete subgraph
* (Minimum) Vertex cover
  1. minimum number of vertices that “touches” all edges

Examples of reductions:

* Using Hamiltonian circuit to solve TSP 🡪
  1. If we had a fast algorithm for TSP, we would also solve Hamiltonian problem
* Using 3SAT to solve Independent Set 🡪 
  1. If we had a fast algorithm for Independent Set, we would also solve 3SAT
* Using Independent Set to solve Clique 🡪
* Using Independent Set to solve Vertex Cover 🡪

## NP-Hard Proofs

* *Theorem*: TSP (Traveling Salesperson Problem) is NP-Hard
* *Proof*: Reduction from Hamiltonian circuit to TSP ()

Wait a minute: TSP is not a decision problem!

No worries. Define as:

* input: complete, undirected, weighted graph
* output: in a Hamiltonian circuit of cost ?

We could try to use all possible values, but is not guaranteed to be polynomial; using only the cycles will not work either.

*What we actually do*: Pick an arbitrary input instance for . and create the following input for TSP:

* complete, undirected, weighted graph with:

If we use this reduction takes poly-time . Then:

* if has an Hamiltonian circuit, then the TSP algorithm run on returns an Hamiltonian circuit with cost
* if doesn’t have a Hamiltonian circuit, then any Hamiltonian circuit in must have edge not in , hence of weight . Hence, in this case, a TSP algorithm run on returns a Hamiltonian circuit of cost

If we had a fast algorithm for TSP we would also solve the Hamiltonian circuit problem.

Reduction from (problem in logic) to (problem in graphs) 🡪

Immagine che contiene testo, diagramma, linea, Carattere

Descrizione generata automaticamenteThey seem totally unrelated problems, but let’s see what we have to do (figure here is from “Algorithms” book of Jeff Erickson, suggested in particular for the whole NP-Hardness chapter):

Immagine che contiene testo, calligrafia, schizzo, disegno

Descrizione generata automaticamenteWhat we are conjecturing is the following:

Basically, the presence of an independent set in the constructed graph corresponds to a satisfying truth assignment for the 3SAT instance.

Let’s see the main ideas (figure representing the scenario):

* pick an arbitrary Boolean formula with clauses
* vertices: each vertex represents one literal in
  1. a *group* of 3 vertices represents a clause (one of the clauses)
     1. assignment request = choose vertices and make a request

Immagine che contiene disegno, schizzo, diagramma, Line art

Descrizione generata automaticamente

* edges:
  1. We add an edge between a literal and its inverse, for all the literals
  2. We add an edge between every pair of vertices that are in the same group

There are two ways to think about 3SAT: (this reasoning coming from [here](https://courses.engr.illinois.edu/cs374/fa2020/lec_prerec/23/23_2_0_0.pdf))

* 1. Find a way to assign 0/1 (false/true) to the variables such that the formula evaluates to true, that is each clause evaluates to true
* 2. Pick a literal from each clause and find a truth assignment to make all of them true. You will fail if two of the literals you pick are in conflict, i.e., you pick and

The reduction works this way:

* the graph will have one vertex for each literal in a clause
* Immagine che contiene schermata

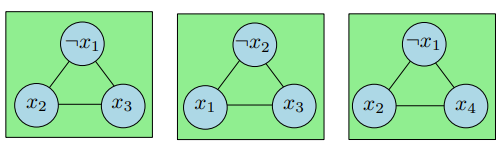
  Descrizione generata automaticamenteconnect the 3 literals in a clause to form a triangle; the independent set will pick at most one vertex from each clause, which will correspond to the literal to be set to true
* connect 2 vertices if they label complementary literals; this ensures that the literals corresponding to the independent set do not have a conflict

Immagine che contiene diagramma, linea, schermata

Descrizione generata automaticamente

* Take to be the number of clauses, ensuring they are all “covered”

Remember what *satisfiable* means:

* Immagine che contiene testo, Carattere, Elementi grafici

  Descrizione generata automaticamenteit asks whether the variables of a given Boolean formula can be consistently replaced by the values TRUE or FALSE in such a way that the formula evaluates to TRUE

1. idea: independent set represents conflicts add an edge between every pair of vertices that are inconsistent (*asking* for opposite assignments to the same variable)
   1. in words: if you choose one vertex, it means it’s part of a clause
   2. you have to choose other two vertices which are sure to be different because they are a different independent set
   3. if you choose one vertex, you have to choose the complement
      1. in order to realize the AND inside the formula

*Observation*: an independent set with vertex in each group gives a satisfying truth assignment should look for indipendent sets of size to say “YES, it’s satisfiable”.

*Issue:* an independent set now is free to recruit multiple vertices from a group, so I might output “YES, is satisfiable” even if this not true! idea: force the recruitment of one vertex per group.

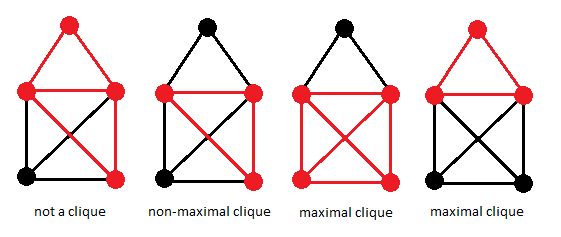
1. add one edge between every pair of vertices that one in the same group

*Claim*: contains an independent set of size exactly the formula is satisfiable

*Proof*:

1. suppose is satisfiable. Pick any satisfying assignment. Each clause in has literal. Thus, we can choose a subset of vertices in that contains exactly one vertex per group such that the corresponding literals are all . The set is an independent set because it does not contain both endpoints of any edge of a group, nor of any edge that connects inconsistent literals (as it is derived from a consistent truth assignment)
2. suppose contains an independent set of size . Each vertex in must be in a different group. Assign to each literal of . Since inconsistent literals are connected by an edge, this assignment is consistent. Since contains verftex per group, each clause in contains (at least) one literal is satisfiable

* (Maximum) Clique: compute the longest complete subgraph
  1. other name for a complete graph (from now on, the problem will be called Clique)
  2. below, a useful figure to clearly see the problem

*Show that Clique is NP-Hard*.

Solution (a nice graphical explanation [here](https://opendsa-server.cs.vt.edu/ODSA/Books/Everything/html/clique_to_independentSet.html))

Immagine che contiene schizzo, disegno, clipart

Descrizione generata automaticamenteDecision version:

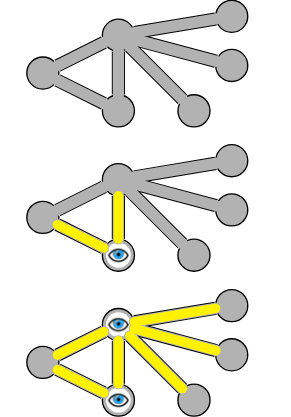
* Input:
* Output: in a clique of size ?

We operate a reduction from Maximum Independent Set (Ham. circuit is not really related to it; as you can see [here](https://www.cs.cmu.edu/~avrim/451f11/lectures/lect1108.pdf), one can use 3SAT in order to show Clique is NP-complete). Figure here shows Independent Set.

* *Intuition*
  1. clique: vertices with all edges between them
  2. maximum independent set: vertices with no edges between them
* *Definition*
  1. given a graph , its edge-complement has the same vertex and an edge set such that (so, no common edges)
* *Observation*
  1. a set of vertices is independent in is a clique in the largest independent set in has the same size as the largest clique in

Immagine che contiene disegno, schizzo, diagramma, Line art

Descrizione generata automaticamenteTo make it super complete, let’s draw the schema of what we are doing – takes time, givemn the constant work needed to traverse all edges *and* vertices:

*Definition*: a vertex cover of a graph is a set of vertices that includes that at least one endpoint of every edge of the graph

* 1. Side figure represents such, to be clearer to you

Another problem is:

* (Minimum) Vertex Cover: compute the smallest vertex in a given graph
  1. From now on, only called Vertex Cover

*Show that Vertex Cover is NP-Hard*.

Solution (once again, a nice graphical explanation of this one [here](https://opendsa-server.cs.vt.edu/ODSA/Books/Everything/html/independentSet_to_vertexCover.html))

Decision version:

* Input:
* Output: in a vertex cover of size ?

We operate a reduction from Maximum Independent Set (once again, this is the most similar problem to the one we are proving)

* *Observation*
  1. a set of vertices is independent in is a vertex cover of
     1. in blue there is an independent set (actually the biggest one)
     2. Immagine che contiene linea, Arte bambini, diagramma, design

        Descrizione generata automaticamentethe other ones are the vertex cover

the longest independent set in has size , where is the size of the smallest vertex cover of

Independent set:

* Input:
* Output: in an independent set of size

Immagine che contiene calligrafia, schizzo, disegno, Line art

Descrizione generata automaticamenteOnce again, let’s represent this in a complete way:

Exercise

* *Show that*:

*these 3 problems are equivalent*.

Solution (official = shorter)

* “same” as
* we can consider the following figure for this one
  1. consider a clique of size 4 in the middle (left)
  2. if you take the complement of this one (right)
* has a clique of size has a vertex over of size
  1. Immagine che contiene linea, schizzo, diagramma

     Descrizione generata automaticamenteproof: see the book (§ - p. 1106 of 4th edition – theorem 34.12)

Solution (longer and better explained)

1. Suppose that we have an efficient algorithm for solving Independent Set, it can simply be used to decide whether has a vertex cover of size at most , by asking it to determine whether G has an independent set of size at least

Given an instance of the Vertex Cover problem, consisting of a graph and an integer representing the size, we construct an instance of the Independent Set problem as follows:

1. Let (i.e., the graph for the Independent Set instance is the same as the original graph G).
2. Let (i.e., the target size of the independent set is the number of vertices in minus the size of the vertex cover ).

To show that this reduction is correct, we need to prove the following:

1. If has a vertex cover of size , then has an independent set of size .
2. If has an independent set of size , then G has a vertex cover of size .

Let’s prove both (1) and (2):

* Suppose is a vertex cover of size in . Then, the set is an independent set in (since covers all the edges, no two vertices in can be adjacent). Furthermore,
* Suppose is an independent set of size in . Then, the set is a vertex cover in (since is independent, every edge must have at least one endpoint in ). Furthermore, .

1. To show that , we need to provide a polynomial-time reduction from the Clique problem to the Vertex Cover problem. Here's one way to construct the reduction:

Given an instance of the Clique problem, consisting of a graph and an integer , we construct an instance of the Vertex Cover problem as follows:

1. Let (i.e., the graph for the Vertex Cover instance is the same as the original graph G).
2. Let (i.e., the target size of the vertex cover is the number of vertices in minus the size of the clique ).

To show that this reduction is correct, we need to prove the following:

1. If has a clique of size , then has a vertex cover of size .
2. If has a vertex cover of size , then has a clique of size .

Proof of (1): Suppose is a clique of size in . Then, the set is a vertex cover in (since is a clique, every edge must have at least one endpoint in ). Furthermore, .

Proof of (2): Suppose is a vertex cover of size in . Then, the set is a clique in (since is a vertex cover, every edge must have both endpoints in , which means is a clique). Furthermore, .

# Approximation Algorithms

These kinds of algorithms are are efficient algorithms that find approximate solutions to optimization problems (in particular NP-hard problems) with *provable* guarantees on the distance of the returned solution to the optimal one. They solve problems not solvable in polynomial time using approximation.

An *optimization problem* can be described as follows:

where approximation problem, = set of inputs and = set of solutions.

Above, the *cost function* maps each solution to a positive real number.

Above, the the *set of feasible solutions*, and our goal follows.

Here, we want to find the best solution for a minimization/maximization problem. Specifically, we want to find it for the specific instance of that problem .

*Definition*: Let be an optimization problem and let be an algorithm for that returns, . We say that has an approximation factor of if such that we have:

* minimization problem (basically, an explicit lower-bound of the optimal solution)
* maximization problem (basically, an explicit upper-bound of the optimal solution)

Here, we assume that maps each feasible solution to a real number .

*Goal*: , with as small as possible.

*Definition*: An approximation scheme for is an algorithm with inputs that is a -approximation.

* In this case we just have to choose *how much approximation* we want by tuning the value of
* In other words: fixed an instance of size , the quality is (whatever is)

## Examples of Approximations

Very first algorithm you can think of? Use a *greedy approach*:

* select the vertex for the highest degree
* “remove” the touched edges
* repeat

Immagine che contiene disegno, diagramma, cerchio, linea

Descrizione generata automaticamenteConsider the following figure – take 3 as the highest, then 2 and 1 and remove touched edges as said:

Unfortunately, for this algorithm .

How to prove a LB (Lower Bound)? It’s enough to show one “bad” input instance.

Another algorithm (greedy approach):

* choose *any* edge
* add its endpoints to the solution
* “remove” the covered edges
* repeat

We’ll show that this is a 2-approximation algorithm.

*Complexity*:

We’ll show

Given = set of selected edges:

* is a matching:
  1. i.e. set of edges with no vertices in common
  2. every edge is disjoint, so there is no couple of edges sharing a common node
* selects a maximal matching: edge is not a matching
  1. this is a matching which cannot be increased
     1. not possible to select an edge which touches other vertices

Immagine che contiene schizzo, disegno, arte

Descrizione generata automaticamente*Proof*:

1. lower bound to the optimal solution

What can one say about ?

is a matching in there must be vertex edge of (right figure)

In whatever vertex cover, particularly , we have to cover all graph edges and, in particular, all edges. But is a matching (so, every edge of is disjoint), so:

2. upper bound to the optimal solution

What can one say about ?

* by construction and so:

(1. + 2.)

# TSP & Metric TSP

## Travelling Salesperson Problem (TSP)

*Definition*: Given a complete, undirected graph and a function , output a tour (i.e. a cycle that passes through every vertex exactly once) minimizing . Collectively:

* : we will work only on positive weights).
  1. We can do this without loss of generality (wlog) because every TSP tour has the same number of edges we can add a large weight to each edge, such that edges have non-negative weights

## Metric TSP

Metric TSP is a special case of TSP where the weight function satisfies the triangle inequality:

it holds that

Immagine che contiene schizzo, disegno

Descrizione generata automaticamenteThe following is an example of that:

The problem can be shown to be NP-Hard, using an instance of TSP to build this one and using an Hamiltonian circuit to show we can assign a weight to each edge being “balanced” overall in the choice, always ensuring the best choice.

### Metric TSP is NP-Hard

*Theorem:*  is NP-Hard

*Proof*:

Immagine che contiene calligrafia, Carattere, linea, bianco

Descrizione generata automaticamenteThe idea is the following (where inequality is not strictly satisfied):

Immagine che contiene calligrafia, testo, Carattere, tipografia

Descrizione generata automaticamente

Given an instance of the TSP problem , we build an instance of such that the triangle inequality is satisfied in . In order to to this, we can define the weight function as follows:

giving

Think of a value in such a way there if there exist an Hamiltonian circuit, there will be one in in such a way the cost of the tour will work for every edge, so:

To be shown yet:

1. satisfies triangle inequality
2. an Hamiltonian circuit of cost in Hamiltonian circuit of cost in

Let’s see how to solve them formally:

1. (is it at most the weight of the others)?

(does this hold adding a general weight)?

(simply adding both members)

(is it true this is at most 0)?



We only ask if the definition of triangle inequality is satisfied correctly.

Note it’s important that the weights of edges are non-negative (otherwise, last part does not hold)

* 1. : Ham. circuit of cost in . Note that an optimal solution contains exactly edges and the same circuit in introduces a weight for every edge (so, edge). Thus, the cost of said tour in is
  2. just remove the edge to obtain a Ham. circuit of cost in

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1. (is it at most the weight of the others)?

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  2. just remove the edge to obtain a Ham. circuit of cost in

## 2-Approximation Algorithm for Metric TSP

What is the most similar problem to ? MST (Minimum Spanning Tree). We give the following *intuition*:

* we give an MST
* we want to build a cycle: what to do on a tree to achieve it?
* basically, there is a DFS traversing all the nodes
* Immagine che contiene diagramma, Carattere, calligrafia, linea

  Descrizione generata automaticamentethe cycle forms having all nodes touched exactly once

We can simply solve this problem by adding the edge ) to the list and make it an Hamiltonian circuit. We are free to add every edge we want because the graph is complete by definition. To do so, we define the following:

This algorithm uses Prim as a subroutine to compute the MST. As such, this is super-fast and can be characterized as a near-linear algorithm.

So, to fully summarize:

1. Given a complete weighted graph , pick any vertex  as the root, and find a minimum spanning tree , using Prim’s algorithm
2. Compile a list  of vertices encountered in a preorder traversal of
3. Return  as a tour

## 3/2 (or 1.5) Approximation Algorithm for Metric TSP

Christofides algorithm (or Christofides–Serdyukov algorithm) was born in 1976.

Reason for 2-approximation factor was the fact the preorder traversal of used every edge of exactly twice. We’ll try to improve on this by constructing a tour that traverses MST edges only once.

We give a couple of definitions useful for this context:

* A path (or cycle) is Eulerian if it crosses every edge of the graph exactly once
* A connected graph is Eulerian if there exists an Eulerian cycle

If the MST was Eulerian (cannot be) then we would have a 1-approx algorithm (which would be optimal, given one would cross every edge exactly once). is finding a “cheap” Eulerian cycle in the MST, but effectively needs to double its edges.

*Question*: is there a cheaper Eulerian cycle?

Immagine che contiene calligrafia, Carattere, bianco, linea

Descrizione generata automaticamente*Theorem*: A connected graph is Eulerian every vertex has even degree. The intuition is the following: enter a vertex, then exiting from it using a new edge, doing that without using edges more than once.

We want to focus on the *odd* degree vertices, given I have to cross again vertices (the even ones are fine, given we don’t pass on them again). So, let’s handle the odd-degree vertices of the MST explicitly.

*Property*: in any (finite) graph, the number of vertices of odd degree is even.

*Proof*: We use the following equality:

Basically, the sum of odd vertices with even ones, will get us an even result, that’s the main intuition. So, we can split such summation into two parts:



Since the result must be even, the sum of degrees must be even too. But this happens only if the number of odd degree vertices is even.

*Idea*: augment the initial MST with (the cheapest basically) a minimum-weight perfect matching (perfect means that it includes all the vertices) between the vertices that have odd degree in the MST.

Immagine che contiene calligrafia, Arte bambini, linea, diagramma

Descrizione generata automaticamenteFor instance, let’s consider the following MST, coloring in blue the odd-degree vertices. Imagine we add a perfect matching colored in red.

the resulting graph has only even-degree vertices, i.e. is an Eulerian graph.

Let’s write the algorithm, which does exactly for things:

Let be the set of vertices of with odd-degree. Compute a min-weight perfect matching on the graph induced by // this can be done in polynomial time (Edmonds, 1965)

The graph is Eulerian // any edge in both and appears twice in this (multi)graph.

Return the cycle that visits all the vertices of in the order of their first appearance in the Eulerian cycle (basically, skipping all repeated vertices – shortcutting)

Immagine che contiene schizzo, disegno, diagramma, Line art

Descrizione generata automaticamenteConsider the following example, connecting all vertices:

Immagine che contiene disegno, diagramma, schizzo, Line art

Descrizione generata automaticamenteNow take the odd-degree vertices and compute the minimum-weight perfect matching .



Putting all of this together (merging it all) we get:

Immagine che contiene schizzo, disegno, Line art, diagramma

Descrizione generata automaticamente

Analysing the algorithm:

* 1. by triangle inequality

The goal to reach is . We would need to prove:

* (by triangle inequality)

We will do the following clever step:

optimal tour of the odd-degree vertices of

Immagine che contiene calligrafia, testo, Carattere

Descrizione generata automaticamente



One of these has cost

Putting all pieces together we get:

# Set Cover

Set cover is an optimization problem that models many problems requiring resources to be allocated. It aims to find the least number of subsets that cover some universal set.

Its inputs are:

* = instance of the set covering problem
* set of elements of any kind, called “universe”
  1. stands for “Boolean”: set of all subsets of

There is a constraint that needs to be always respected: i.e., “ covers ”

Optimization problem: (smallest subset of having its members covering all ) 🡪 find s.t.

1. covers

*Example*:

## Set Cover is NP-Hard

*Assertion*: Set Cover (in its decision version ) is NP-hard.

*Proof*:

* Given an instance of Vertex Cover Problem
* we create an instance of Set Cover problem

Basically

where:

* one vertex ,
* such that or , which is the set of covered edges by node

Basically, there are subsets , and each subset is the set of edges incident to vertex . Now show that finding a Set Cover of size finding a Vertex Cover of size .

* Suppose is a set cover for . Then, every edge in must be incident to at least one vertex . This happens because every element if one node of the adjacency list and so we find the minimal number of nodes touching all edges of graph, guaranteeing it will be minimal (for all sizes, given, even if less than ). Therefore, it forms a vertex cover of size in .
* Suppose is a vertex cover in . Then, covers all the edges incident to vertex . Therefore, is a set cover of size for

## Greedy Approximation Algorithm

The greedy method works by picking at each stage, the set that covers the greatest number of remaining elements that are uncovered:

* choose the subset that contains the largest number of uncovered elements
* remove from those covered elements
* repeat until

*Correctness*: (it does the job – it covers all the elements) At every iteration decreases by at least one.

*Complexity*:

* n. of iterations (every contains at least an element)
* n. of iterations (every contains at least two elements)
* n. of iterations
* iterations the complexity is (scanning all elements and decreasing elements in both sets)

# Randomized Algorithms

Randomized algorithms are algorithms that may do *random* choices, basically using a source of randomness in its logic. We give some basic examples:

* Example 1: Randomized quicksort (RQS)

Quicksort but chooses the pivot at random so to break the unlucky element choice and get on average a good probability on result.

* Example 2: Verifying polynomial identity

Checks if polynomials are equivalent and there are different approaches:

* check all the terms (slow)
* choose a random integer, compute the polynomials and check if they are equal
  1. it may be wrong, outputting YES even If they are different

## Classification of Randomized Algorithms

We divide these into two main categories:

1. randomized algorithms that never fail, which are called “LAS VEGAS” algorithms
   1. (e.g., randomized quicksort)

where is the decisional problem, is an input instance, is the random algorithm which applied to the input instance produces a solution s.t. the couple belongs to

Randomness comes into play in the analysis of the complexity – because it depends from the randomness of the choices. is a random variable of which we usually study its expectation or (so, for some constants and , we say that with high probability (here, is called complexity function) – this second one is more powerful than the first, so more powerful than .

1. randomized algorithms that may fail are called “MONTE CARLO” algorithms
   1. e.g., verifying polynomial identities

We study as a function of 🡪 family of random variables (binary)

Moreover, even may be a random variable. For decision problems, these algorithms can be divided into:

* one-sided: they may fail only on one answer
  1. e.g., can make right all YES instances but may be wrong on all NO instances
* two-sided: they may fail in both answers
  1. e.g., it can make wrong all YES instances but can make wrong all NO instances