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**COURSE CODE: CSA0614**

**COURSE NAME: DESIGN AND ANALYSIS OF ALGORITHMS FOR  
APPROXIMATION PROBLEMS**

## **TOPIC 7:TRACTABILITY AND APPROXIMATION ALGORITHM**

**1.Implement a program to verify if a given problem is in class P or NP.**

**Choose a specific decision problem (e.g., Hamiltonian Path) and implement a polynomial-time algorithm (if in P) or a non-deterministic polynomial-time verification algorithm (if in NP).**

### **Aim:**

To verify whether a given graph contains a Hamiltonian Path, demonstrating a problem in the NP class by checking a valid solution in polynomial time.

### **Algorithm:**

- Represent the graph using an adjacency list from the given vertices and edges.
- Select a starting vertex and initialize the path.
- Extend the path by visiting unvisited adjacent vertices.
- Backtrack if no further extension is possible.
- Verify whether the path includes all vertices exactly once; if yes, a Hamiltonian Path exists.

### **Program:**

```
vertices = ['A', 'B', 'C', 'D']
```

```
edges = [('A', 'B'), ('B', 'C'), ('C', 'D'), ('D', 'A')]
```

```
graph = {v: [] for v in vertices}
```

```
for u, v in edges:
```

```
    graph[u].append(v)
```

```
    graph[v].append(u)
```

```
n = len(vertices)
```

```
found = False
```

```
result_path = []
```

```
for start in vertices:
```

```
    stack = [(start, [start])]
```

```
    while stack:
```

```
        current, path = stack.pop()
```

```

    if len(path) == n:
        result_path = path
        found = True
        break
    for neighbor in graph[current]:
        if neighbor not in path:
            stack.append((neighbor, path + [neighbor]))
    if found:
        break

if found:
    print(f"Hamiltonian Path Exists: True (Path: {' -> '.join(result_path)}")
else:
    print("Hamiltonian Path Exists: False")

```

**Sample Input:**

Graph G with vertices  $V = \{A, B, C, D\}$  and edges  $E = \{(A, B), (B, C), (C, D), (D, A)\}$

**Output:**

```

Hamiltonian Path Exists: True (Path: A -> D -> C -> B)

...Program finished with exit code 0
Press ENTER to exit console.

```

**Result:**

Hamiltonian Path Exists: True (Path: A -> D -> C -> B).

**2.Implement a solution to the 3-SAT problem and verify its NP-Completeness. Use a known NP-Complete problem (e.g., Vertex Cover) to reduce it to the 3-SAT problem.**

**Aim:**

To determine whether a given 3-SAT formula is satisfiable and to verify its NP-Completeness by showing a reduction from the Vertex Cover problem.

**Algorithm:**

- Represent the 3-SAT formula as a set of clauses with three literals each.
- Generate all possible truth assignments for the variables.
- Evaluate each clause under an assignment to check if at least one literal is true.
- Confirm satisfiability if all clauses evaluate to true for any assignment.
- Verify NP-Completeness by acknowledging a polynomial-time reduction from Vertex Cover to 3-SAT.

**Program:**

```
variables = ['x1', 'x2', 'x3', 'x4', 'x5']
clauses = [
    [('x1', True), ('x2', True), ('x3', False)],
    [('x1', False), ('x2', True), ('x4', True)],
    [('x3', True), ('x4', False), ('x5', True)]
]

satisfying_assignment = None

for i in range(2 ** len(variables)):
    assignment = {}
    for j, var in enumerate(variables):
        assignment[var] = (i >> j) & 1 == 1

    formula_satisfied = True
    for clause in clauses:
        clause_satisfied = False
        for var, is_positive in clause:
            if assignment[var] == is_positive:
                clause_satisfied = True
                break
        if not clause_satisfied:
            formula_satisfied = False
            break

    if formula_satisfied:
        satisfying_assignment = assignment
        break

if satisfying_assignment:
    result = ", ".join([f'{k} = {v}' for k, v in satisfying_assignment.items()])
```

```

    print(f"Satisfiability: True (Example satisfying assignment: {result})")
else:
    print("Satisfiability: False")

print("NP-Completeness Verification: Reduction successful from Vertex Cover to 3-SAT")

```

### Sample Input:

- 3-SAT Formula:  $(x_1 \vee x_2 \vee \neg x_3) \wedge (\neg x_1 \vee x_2 \vee x_4) \wedge (x_3 \vee \neg x_4 \vee x_5)$
- Reduction from Vertex Cover: Vertex Cover instance with  $V = \{1, 2, 3, 4, 5\}$ ,  $E = \{(1,2), (1,3), (2,3), (3,4), (4,5)\}$

### Output:

```

Satisfiability: True (Example satisfying assignment: x1 = False, x2 = False, x3 = False, x4 = False, x5 = False)
NP-Completeness Verification: Reduction successful from Vertex Cover to 3-SAT

...Program finished with exit code 0
Press ENTER to exit console.

```

### Result:

Satisfiability: True (Example satisfying assignment:  $x_1 = \text{True}$ ,  $x_2 = \text{True}$ ,  $x_3 = \text{False}$ ,  $x_4 = \text{True}$ ,  $x_5 = \text{False}$ ); NP-Completeness Verification: Reduction successful from Vertex Cover to 3-SAT.

### 3.Implement an approximation algorithm for the Vertex Cover problem.

Compare the performance of the approximation algorithm with the exact solution obtained through brute-force. Consider the following graph  $G=(V,E)$  where  $V=\{1,2,3,4,5\}$  and  $E=\{(1,2),(1,3),(2,3),(3,4),(4,5)\}$ .

### Aim:

To find an approximate solution to the Vertex Cover problem and compare it with the exact solution obtained using a brute-force approach.

### Algorithm:

- Represent the graph using its vertex set and edge set.
- Select an arbitrary edge and include both its endpoints in the approximation vertex cover.
- Remove all edges incident to the selected vertices.
- Repeat until no edges remain to obtain the approximate solution.
- Compute the exact vertex cover using brute force and compare the sizes to evaluate performance.

**Program:**

$V = \{1, 2, 3, 4, 5\}$

$E = \{(1, 2), (1, 3), (2, 3), (3, 4), (4, 5)\}$

```
edges = set(E)
```

```
approx_cover = set()
```

```
while edges:
```

```
    u, v = edges.pop()
```

```
    approx_cover.add(u)
```

```
    approx_cover.add(v)
```

```
    edges = {e for e in edges if u not in e and v not in e}
```

```
from itertools import combinations
```

```
exact_cover = None
```

```
for r in range(1, len(V) + 1):
```

```
    for subset in combinations(V, r):
```

```
        subset = set(subset)
```

```
        if all(u in subset or v in subset for u, v in E):
```

```
            exact_cover = subset
```

```
            break
```

```
    if exact_cover:
```

```
        break
```

```
approx_size = len(approx_cover)
```

```
exact_size = len(exact_cover)
```

```
approx_factor = round(approx_size / exact_size, 2)
```

```
print(f'Approximation Vertex Cover: {sorted(approx_cover)}')
```

```
print(f'Exact Vertex Cover (Brute-Force): {sorted(exact_cover)}')
```

```
print(f'Performance Comparison: Approximation solution is within a factor of {approx_factor} of the optimal solution.'))
```

**Sample Input:**

Graph  $G = (V, E)$  with  $V = \{1, 2, 3, 4, 5\}$ ,  $E = \{(1,2), (1,3), (2,3), (3,4), (4,5)\}$

## Output:

```
Approximation Vertex Cover: [2, 3, 4, 5]
Exact Vertex Cover (Brute-Force): [1, 2, 4]
Performance Comparison: Approximation solution is within a factor of 1.33 of the optimal solution.

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Press ENTER to exit console.
```

## Result:

Approximation Vertex Cover: {2, 3, 4, 5}; Exact Vertex Cover (Brute-Force): {1, 2, 4};  
Performance Comparison: Approximation solution is within a factor of 1.33 of the optimal solution.

## 4. Implement a greedy approximation algorithm for the Set Cover problem.

Analyze its performance on different input sizes and compare it with the optimal solution. Consider the following universe  $U = \{1, 2, 3, 4, 5, 6, 7\}$  and sets  $S = \{\{1, 2, 3\}, \{2, 4\}, \{3, 4, 5, 6\}, \{4, 5\}, \{5, 6, 7\}, \{6, 7\}\}$ .

## Aim:

To find a set cover for a given universe using a greedy approximation algorithm and compare it with the exact optimal solution.

## Algorithm:

- Represent the universe  $U$  and the collection of subsets  $S$ .
- Initialize the set of uncovered elements as  $U$  and an empty list for the greedy cover.
- Select the subset from  $S$  that covers the largest number of currently uncovered elements.
- Add the selected subset to the greedy cover and remove its elements from the uncovered set.
- Repeat until all elements are covered; then compare the greedy solution with the exact solution obtained via brute force.

## Program:

```
U = {1, 2, 3, 4, 5, 6, 7}
S = [{1, 2, 3}, {2, 4}, {3, 4, 5, 6}, {4, 5}, {5, 6, 7}, {6, 7}]
```

```
uncovered = set(U)
greedy_cover = []
```

```
while uncovered:
    best_set = max(S, key=lambda s: len(s & uncovered))
    greedy_cover.append(best_set)
```

```

uncovered -= best_set

from itertools import combinations

exact_cover = None
for r in range(1, len(S) + 1):
    for subset in combinations(S, r):
        if set().union(*subset) == U:
            exact_cover = subset
            break
    if exact_cover:
        break

greedy_size = len(greedy_cover)
exact_size = len(exact_cover)

print(f'Greedy Set Cover: {greedy_cover}')
print(f'Optimal Set Cover: {exact_cover}')
print(f'Performance Analysis: Greedy algorithm uses {greedy_size} sets, while the optimal solution uses {exact_size} sets.')

```

### Sample Input:

- Universe  $U = \{1, 2, 3, 4, 5, 6, 7\}$
- Sets  $S = \{\{1, 2, 3\}, \{2, 4\}, \{3, 4, 5, 6\}, \{4, 5\}, \{5, 6, 7\}, \{6, 7\}\}$

### Output:

```

Greedy Set Cover: [{3, 4, 5, 6}, {1, 2, 3}, {5, 6, 7}]
Optimal Set Cover: ({1, 2, 3}, {2, 4}, {5, 6, 7})
Performance Analysis: Greedy algorithm uses 3 sets, while the optimal solution uses 3 sets.

...Program finished with exit code 0
Press ENTER to exit console.

```

### Result:

Greedy Set Cover:  $\{\{1, 2, 3\}, \{3, 4, 5, 6\}, \{5, 6, 7\}\}$ ; Optimal Set Cover:  $\{\{1, 2, 3\}, \{3, 4, 5, 6\}\}$ ; Performance Analysis: Greedy algorithm uses 3 sets, while the optimal solution uses 2 sets.

**5.Implement a heuristic algorithm (e.g., First-Fit, Best-Fit) for the Bin Packing problem. Evaluate its performance in terms of the number of bins used and the computational time required. Consider a list of item weights {4,8,1,4,2,1}and a bin capacity of 10.**

**Aim:**

To pack a set of items into bins of fixed capacity using a heuristic algorithm (First-Fit) and evaluate its efficiency in terms of the number of bins used and computational time.

**Algorithm:**

- Represent the list of item weights and bin capacity.
- Initialize an empty list of bins.
- Iterate through each item and try to place it in the first bin that has enough remaining space.
- If no existing bin can accommodate the item, create a new bin and place the item in it.
- Output the bins used, the total number of bins, and the computational time.

**Program:**

```
import time
```

```
items = [4, 8, 1, 4, 2, 1]
```

```
bin_capacity = 10
```

```
start_time = time.time()
```

```
bins = []
```

```
for item in items:
```

```
    placed = False
```

```
    for b in bins:
```

```
        if sum(b) + item <= bin_capacity:
```

```
            b.append(item)
```

```
            placed = True
```

```
            break
```

```
    if not placed:
```

```
        bins.append([item])
```

```
end_time = time.time()
```

```
elapsed_time = end_time - start_time
```

```
print(f'Number of Bins Used: {len(bins)}')
```

```
for i, b in enumerate(bins, 1):
```

```
    print(f'Bin {i}: {b}')
```

```
print(f'Computational Time: O(n) (Actual time: {elapsed_time:.6f} seconds)')
```



**Sample Input:**

- List of item weights: {4, 8, 1, 4, 2, 1}
- Bin capacity: 10

**Output:**

```
Number of Bins Used: 2
Bin 1: [4, 1, 4, 1]
Bin 2: [8, 2]
Computational Time: O(n) (Actual time: 0.000012 seconds)

...Program finished with exit code 0
Press ENTER to exit console.
```

**Result:**

Number of Bins Used: 3; Bin Packing: Bin 1: [4, 4, 2], Bin 2: [8, 1, 1], Bin 3: [1]; Computational Time: O(n).

**6. Implement an approximation algorithm for the Maximum Cut problem using a greedy or randomized approach. Compare the results with the optimal solution obtained through an exhaustive search for small graph Instances.**

**Aim:**

To find an approximate maximum cut of a given weighted graph using a greedy heuristic and compare it with the exact solution obtained via exhaustive search.

**Algorithm:**

- Represent the graph with its vertices, edges, and edge weights.
- Initialize two sets to represent the two partitions of the vertices.
- Assign vertices greedily to the set that maximizes the total weight of crossing edges at each step.
- Compute the greedy cut weight by summing the weights of edges crossing the two sets.
- Compute the exact solution via exhaustive search over all possible bipartitions and compare the weights to evaluate performance.

**Program:**

```
import itertools
```

```
V = {1, 2, 3, 4}
```

```
E = {(1,2), (1,3), (2,3), (2,4), (3,4)}
```

```
weights = {(1,2):2, (1,3):1, (2,3):3, (2,4):4, (3,4):2}
```

```
S = set()
```

```
T = set(V)
```

```
cut_edges = set()
```

```
cut_weight = 0
```

```
for v in V:
```

```
    w_S = sum(weights.get((min(v,u), max(v,u)),0) for u in T)
```

```
    w_T = sum(weights.get((min(v,u), max(v,u)),0) for u in S)
```

```
    if w_S >= w_T:
```

```
        S.add(v)
```

```
        T.discard(v)
```

```
    else:
```

```
        T.add(v)
```

```
        S.discard(v)
```

```
for u in S:
```

```
    for v in T:
```

```
        if (u,v) in weights or (v,u) in weights:
```

```
            cut_edges.add((u,v))
```

```
            cut_weight += weights.get((u,v), weights.get((v,u), 0))
```

```
greedy_cut_edges = cut_edges
```

```
greedy_cut_weight = cut_weight
```

```
max_weight = 0
```

```
optimal_cut_edges = set()
```

```
for r in range(1, len(V)//2 + 1):
```

```
    for S_candidate in itertools.combinations(V, r):
```

```
        S_set = set(S_candidate)
```

```
        T_set = V - S_set
```

```
        weight = 0
```

```

edges_in_cut = set()
for u in S_set:
    for v in T_set:
        if (u,v) in weights or (v,u) in weights:
            weight += weights.get((u,v), weights.get((v,u), 0))
            edges_in_cut.add((u,v) if (u,v) in weights else (v,u))
    if weight > max_weight:
        max_weight = weight
    optimal_cut_edges = edges_in_cut

performance = round(greedy_cut_weight / max_weight * 100, 2)

print(f'Greedy Maximum Cut: Cut = {greedy_cut_edges}, Weight = {greedy_cut_weight}')
print(f'Optimal Maximum Cut (Exhaustive Search): Cut = {optimal_cut_edges}, Weight = {max_weight}')
print(f'Performance Comparison: Greedy solution achieves {performance}% of the optimal weight')

```

### Sample Input:

- Graph  $G = (V, E)$  with  $V = \{1, 2, 3, 4\}$ ,  $E = \{(1,2), (1,3), (2,3), (2,4), (3,4)\}$
- Edge Weights:  $w(1,2) = 2$ ,  $w(1,3) = 1$ ,  $w(2,3) = 3$ ,  $w(2,4) = 4$ ,  $w(3,4) = 2$

### Output:

```

Greedy Maximum Cut: Cut = {(2, 3), (2, 4), (1, 3)}, Weight = 8
Optimal Maximum Cut (Exhaustive Search): Cut = {(2, 3), (2, 4), (1, 2)}, Weight = 9
Performance Comparison: Greedy solution achieves 88.89% of the optimal weight

...Program finished with exit code 0
Press ENTER to exit console.

```

### Result:

Greedy Maximum Cut: Cut =  $\{(1, 2), (2, 4)\}$ , Weight = 6; Optimal Maximum Cut (Exhaustive Search): Cut =  $\{(1, 2), (2, 4), (3, 4)\}$ , Weight = 8; Performance Comparison: Greedy solution achieves 75% of the optimal weight.