

# PROJECT REPORT

---

## A Comparative Analysis of AI Search Algorithms for Real-World Navigation

**Course:** Introduction to Artificial Intelligence

**Team:** The Wayfinders

**Members:** Youssef, Salma, Huda, Yomna, Mahmoud, and Mohammed.

**Submission Date:** December 19, 2025

**GitHub Repository:** [🌐 GitHub - youssef-darrag/real-world-path-visualizer](https://github.com/youssef-darrag/real-world-path-visualizer)

## Executive Summary

This report details the implementation and analysis of six fundamental AI search algorithms applied to real-world pathfinding problems. The MapPath Visualizer application demonstrates how Breadth-First Search (BFS), Depth-First Search (DFS), Depth-Limited Search (DLS), Iterative Deepening Search (IDS), Uniform-Cost Search (UCS), and A\* Search perform on actual geographical maps using OpenStreetMap data. Our analysis reveals significant differences in algorithm performance, particularly highlighting the efficiency gains achieved through heuristic guidance in A\* Search.

# System Architecture

## Technology Stack:

- Core Language: Python 3.8
- GUI Framework: Tkinter with TkinterMapView extension
- Map Processing: OSMnx 1.6.0
- Graph Operations: NetworkX 3.1

## Data Flow Pipeline:

1. Map Acquisition: Download street network from OpenStreetMap
2. Graph Conversion: Convert to NetworkX graph with edge weights
3. Algorithm Execution: Run selected search algorithm
4. Visualisation: Display step-by-step exploration on map
5. Metrics Collection: Track performance statistics

# Algorithm Implementations

## Breadth-First Search (BFS)

```
def bfs_search(graph, start, goal):
    queue = deque([(start, [start])])
    visited = set([start])

    while queue:
        current, path = queue.popleft()
        if current == goal:
            return path
        for neighbor in graph.neighbors(current):
            if neighbor not in visited:
                visited.add(neighbor)
                queue.append((neighbor, path + [neighbor]))
    return None
```

*Features: FIFO queue, complete, optimal for unweighted graphs*

## Depth-First Search (DFS) & Depth-Limited Search (DLS)

```
def dfs(graph, start, goal, depth_limit=None):
    stack = [(start, [start], 0)]
    visited = set()

    while stack:
        node, path, depth = stack.pop()

        if node == goal:
            return path

        if depth_limit and depth >= depth_limit:
            continue

        if node not in visited:
            visited.add(node)
            for neighbor in graph.neighbors(node):
                stack.append((neighbor, path + [neighbor], depth + 1))
```

*Features: LIFO stack, incomplete, not optimal, memory efficient*

## Iterative Deepening Search (IDS)

```
def iterative_deepening(graph, start, goal, max_depth=100):
    for depth in range(max_depth):
        result = depth_limited_search(graph, start, goal, depth)
        if result is not None and result != "CUTOFF":
            return result
    return None
```

*Features: Combines BFS completeness with DFS memory efficiency*

## Uniform-Cost Search (UCS)

```
def uniform_cost_search(graph, start, goal):
    frontier = PriorityQueue()
    frontier.put((0, start, [start]))
    explored = set()

    while not frontier.empty():
        cost, current, path = frontier.get()
        if current == goal:
            return path, cost
        if current not in explored:
            explored.add(current)
            for neighbor in graph.neighbors(current):
                new_cost = cost + graph[current][neighbor]['weight']
                frontier.put((new_cost, neighbor, path + [neighbor]))
    return None, float('inf')
```

*Features: Priority queue, optimal for weighted graphs*

## A Search\*

```
def a_star_search(graph, start, goal, heuristic):
    frontier = PriorityQueue()
    frontier.put((heuristic(start, goal), 0, start, [start]))
    g_costs = {start: 0}

    while not frontier.empty():
        _, g_cost, current, path = frontier.get()
        if current == goal:
            return path, g_cost
        for neighbor in graph.neighbors(current):
            new_g = g_cost + graph[current][neighbor]['weight']
            if neighbor not in g_costs or new_g < g_costs[neighbor]:
                g_costs[neighbor] = new_g
                f_cost = new_g + heuristic(neighbor, goal)
                frontier.put((f_cost, new_g, neighbor, path + [neighbor]))
    return None, float('inf')
```

Features:  $f(n) = g(n) + h(n)$ , heuristic: Euclidean distance

## Visualization System

- Real-time map display with OpenStreetMap tiles
- Color-coded visualization:
  - Green: Start node
  - Red: Goal node
  - Blue: Explored nodes
  - green: Frontier nodes
  - Purple: Optimal path
- Interactive controls: Play, reset, random selection
- Statistics panel: Real-time performance metrics

# Algorithm Analysis

## Theoretical Analysis

Algorithm	Complete	Optimalit y	TC	SC
BFS	Yes	Yes*	$O(b^d)$	$O(b^d)$
DFS	No	No	$O(b^m)$	$O(bm)$
DLS	No	No	$O(b^l)$	$O(bl)$
IDS	Yes	Yes*	$O(b^d)$	$O(bd)$
UCS	Yes	Yes	$O(b^{(C^*/\epsilon)})$	$O(b^{(C^*/\epsilon)})$
A*	Yes	Yes**	$O(b^d)$	$O(b^d)$

\*Optimal for unweighted graphs only

\*With admissible heuristic

**TC** = time Complexity

**SC** = space Complexity

**b** = branching factor

**d** = depth

**m** = maximum depth

**l** = depth limit

**C\*** = Optimal solution cost

**ε** = minimum edge cost

# Practical Behavior Observations

## **BFS Behavior:**

- Expands uniformly in all directions
- Guarantees shortest path in terms of node count
- Performs poorly on weighted graphs
- High memory consumption on dense graphs

## **DFS Behavior:**

- Tends to explore deep branches first
- Can get stuck in infinite loops without cycle checking
- Memory efficient but often finds suboptimal paths
- Performs poorly on graphs with many dead ends

## **UCS Behavior:**

- Systematically expands cheapest paths first
- Optimal for weighted graphs but slower than A\*
- Frontier grows quickly in complex graphs
- Requires edge weight information

## **A\* Behavior:**

- Guided directly toward goal by heuristic
- Most efficient with good heuristic
- Balance between exploration and exploitation
- Performance depends heavily on heuristic quality

# Performance Comparison

## Experimental Setup

### Test Environment:

- Hardware: ryzen 5 5500, 16GB RAM
- Software: Arch linux, Python 3.8
- Test Maps: Three urban areas of varying complexity
- Map Sizes: Small (100 nodes), Medium (500 nodes), Large (1000+ nodes)

### Metrics Collected:

1. Execution time (milliseconds)
2. Nodes explored before solution
3. Path length (meters)
4. Memory Usage
5. Solution optimality (compared to ground truth)

## Performance Results: Table 1: Small Map Performance (100 nodes)

Algorithm	Time (ms)	Nodes Explored	Path Length	Memory Usage	Optimal?
BFS	45	62	850m	85	No
DFS	32	28	1200m	42	No
DLS (d=15)	38	35	-	45	-
IDS	52	65	850m	55	Yes
UCS	68	48	780m	72	Yes
A*	25	18	780m	30	Yes



Table 2: Medium Map Performance (500 nodes)

Algorithm	Time (ms)	Nodes Explored	Path Length	Memory Usage	Optimal?
BFS	210	285	1450m	320	No
DFS	155	142	2100m	180	No
DLS (d=25)	165	158	-	195	-
IDS	245	290	1450m	210	Yes
UCS	320	210	1320m	285	Yes
A*	95	65	1320m	85	Yes

Table 3: Large Map Performance (1000+ nodes)

Algorithm	Time (ms)	Nodes Explored	Path Length	Memory Usage	Optimal?
BFS	520	642	2100m	750	No
DFS	380	325	2850m	420	No
DLS (d=40)	420	385	-	480	-
IDS	580	655	2100m	520	Yes
UCS	780	485	1980m	650	Yes
A*	185	128	1980m	165	Yes

# Key Performance Insights

## Time Efficiency Ranking:

1. A\* (Fastest - heuristic guidance)
2. DFS (Depth-first exploration)
3. DLS (Controlled depth)
4. BFS (Systematic but exhaustive)
5. IDS (Repeated depth-limited searches)
6. UCS (Cost-based, computationally intensive)

## Memory Efficiency Ranking:

1. DFS/DLS (Depth-based, smaller frontier)
2. A\* (Heuristic-guided frontier)
3. IDS (Depth-limited memory usage)
4. UCS (Priority queue management)
5. BFS (Large frontier storage)

## Solution Quality:

- UCS and A\* consistently found optimal paths
- BFS and IDS optimal only for unweighted paths
- DFS often found significantly longer paths
- DLS sometimes failed to find solution within depth limit

# Real-World Considerations

## Urban Network Characteristics Affecting Performance:

1. **Branching Factor Variation:** Intersections vs. straight roads
2. **Dead Ends:** Challenge DFS and DLS
3. **Weight Distribution:** Affects UCS and A\*
4. **Geographical Constraints:** Rivers, parks create search barriers
5. **Network Density:** Dense urban vs. sparse suburban

# Project Achievements

**Complete Implementation:** All six algorithms correctly implemented

**Real-World Integration:** Successful use of OpenStreetMap data

**Educational Visualization:** Clear step-by-step algorithm display

**Performance Analysis:** Comprehensive metrics collection

**Comparative Insights:** Clear algorithm trade-off analysis

# Team Contributions

- **Youssef** : Algorithm implementation (A\*), testing and document integration
- **Salma** : Algorithm implementation (DFS & DLS) and testing integration
- **Huda** : Algorithm implementation (BFS & IDS), testing and document integration.
- **Yomna** : Algorithm implementation (UCS), testing and control integration
- **Mahmoud** : GUI, real-map visualization system and testing analysis
- **Mohamed** : Grid-visualization and performance analysis