Visualising and revewing various pathfinding algorithms on real world streets

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1 Project Synopsis:

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1.0.1 Overview

This project aims to visualize and compare various pathfinding algorithms using real-world geographical data. Leveraging the capabilities of the `OSMNX` and `NETWORKX` libraries, the project provides a robust framework to analyze and display the efficiency and effectiveness of different algorithms on urban road networks.

1.0.2 Key Components

1. **OSMNX**:
   - **Purpose**: To download / process geographical data from OpenStreetMap (OSM).
   - **Functionality**: Extracts street networks, building footprints, and other relevant spatial data. This data forms the basis for our graph-based pathfinding analysis.
2. **NETWORKX**:
   - **Purpose**: To implement and visualize graph-based algorithms.
   - **Functionality**: Provides a range of graph algorithms and visualization tools. For this project, it is used to implement and display pathfinding algorithms such as Dijkstra's, A*, and Breadth-First Search (BFS).

1.0.3 Features

- **Graph Creation**: Convert street network data into a graph format suitable for pathfinding algorithms using NETWORKX.
- **Algorithm Implementations**:
  - **Dijkstra's Algorithm**: Finds the shortest path between nodes based on edge weights (e.g., distance or travel time).
  - **A* Algorithm**: An extension of Dijkstra's that uses heuristics to efficiently find the shortest path.
  - **Breadth-First Search (BFS)**: Explores nodes level-by-level to find the shortest path in unweighted graphs.
- **Visualization**:
  - **Interactive Maps**: Use matplotlib and folium for visualizing the graph and the paths found by the algorithms on an interactive map.

- **Node and Path Highlighting**: Highlight nodes, edges, and paths to provide clear visual feedback on the results of different algorithms.
- **Performance Metrics**: Display metrics such as path length, travel time, and computational efficiency to compare algorithm performance.

1.0.4 Installation and Setup

To run the project, ensure you have the following Python packages installed: - `osmnx` - `networkx` - `matplotlib` - `folium` - `ipyleaflet` - `ipywidgets` - `haversine` - `heapq` (for priority queue implementation)

Install the required packages using pip: "'bash pip install osmnx networkx matplotlib folium ipywidgets ipyleaflet

[1]:
```
import osmnx as ox
from shapely.geometry import LineString, mapping
import geopandas as gpd
from ipyleaflet import *
import timeit
import ipywidgets as widgets
from queue import *
from collections import deque
from ipywidgets import Layout
from IPython.display import display, Image
from haversine import haversine
from sklearn.neighbors import BallTree
import heapq
import pickle
```

2 Real-life Street Data Modeling Using Multigraphs

2.1 Streets as Edges and Intersections as Nodes:

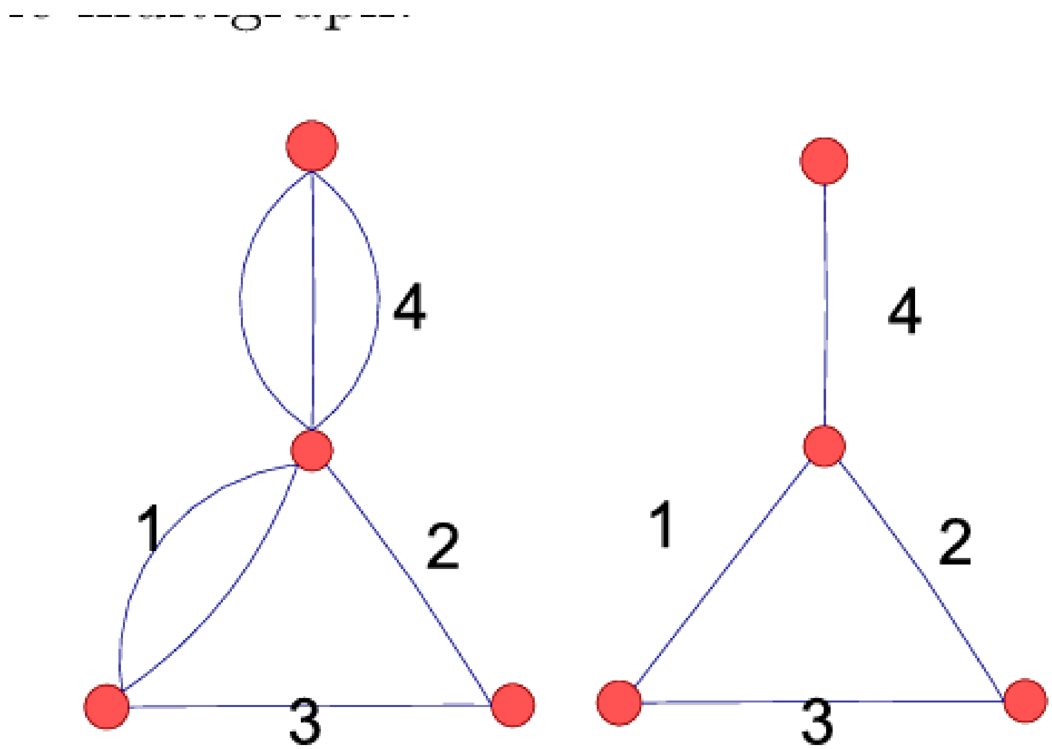
In real life, streets and roads can be thought of as edges in a graph, while intersections, where roads meet, are represented as nodes. Each street segment connecting two intersections becomes an edge in the graph.

2.2 Multigraph Representation:

Real-life street networks often involve multiple edges between the same two nodes. For example, in cities with bidirectional streets or overpasses, multiple streets may connect the same pair of intersections (nodes). This requires the use of a multigraph structure. In a multigraph, multiple edges between the same two nodes are allowed, which accurately represents real-world road networks where multiple connections exist between the same locations. For instance, a two-way street would be modeled as two edges (one for each direction), and highways with parallel service roads would be modeled with separate edges.

2.3 Graph Analysis:

`networkx` allows for various graph-based operations, such as shortest-path algorithms, connectivity analysis, or centrality measures, which are valuable for tasks like route planning, finding the most important streets, or analyzing traffic flows. By leveraging networkx, OSMnx can build detailed models of urban road networks and apply these operations efficiently.



2.3.1 Visualiising the nodes and their data using leaflet and matplotlib

[2]:
```
graph = ox.graph_from_address("texas", network_type = 'drive',dist=10000)
geodf_edge = ox.convert.graph_to_gdfs(
    graph, nodes=False, edges=True, node_geometry=False,
    fill_edge_geometry=True)

ox.plot_graph(graph,close=False,edge_color="#d4af37",node_size=5,node_color="#f9f1f1")
geodf_edge.explore()
```

[2]: <folium.folium.Map at 0x7f351299fb60>

2.4 Visualising pathfinding over various (user-inputted) locations

2.4.1 Setting up global variables

These variables define the initial variables used to set up a user interface for visualizing and interacting with street networks on a map. The main features include:

Map Setup

- **Base Map**: Utilizes OpenStreetMap tiles as the base map.
- **Graph Data**: Manages street network data (nodes and edges) representing city streets, with preloaded street data for specific cities (e.g., Kolkata).

Interactive Markers

- **Start Marker**: Blue circular marker used to set the starting location on the map.
- **End Marker**: Red circular marker used to set the destination location on the map.

Customization Controls

- **Color Pickers**: Allows users to customize the color of paths and nodes displayed on the map.
- **Node Visualization**: Checkbox control to enable/disable the visualization of nodes (with a performance warning due to potential slowness).

Statistics Display

- Widgets are included to display:
  - **Time**
  - **Count**
  - **Distance**
  - **Travel Time Taken**

Responsive Layout

- The interface integrates several controls (e.g., color pickers, checkboxes, labels) into the map using a flexible layout system. This ensures that the map is interactive and customizable for users.

[3]:
```
graph = nodes = edges = center = m = from_marker = to_marker = box = dropdown =␣
↪show_nodes = None
base = basemap_to_tiles(basemaps.OpenStreetMap.Mapnik)
loading = True

preloaded = {"kolkata": "preloaded_graphs/kolkata.pickle"}


mapLayout=Layout(width='98%', height='690px')

from_marker_style = AwesomeIcon(
                        name='circle',
                        icon_color='white',
                        marker_color='blue',
                        spin=False
                        )

to_marker_style = AwesomeIcon(
                    name='circle',
                    icon_color='white',
                    marker_color='red',
                    spin=False
                    )
```

```
color_layout = widgets.Layout(width='240px')

path_color = widgets.ColorPicker(
                concise=False,
                description='Path Colour:',
                value='black',
                disabled=False,
                layout = color_layout
                )

path_control = WidgetControl(widget=path_color, position='bottomright')

node_color = widgets.ColorPicker(
                concise=False,
                description='Node Colour:',
                value='red',
                disabled=False,
                layout = color_layout
                )

node_control = WidgetControl(widget=node_color, position='bottomright')

show_nodes = widgets.Checkbox(value=False,description='Visualise Nodes (SLOW)')
show_node_control = WidgetControl(widget=show_nodes,position='bottomright',disabled=False)


time_label = widgets.Label(value="")
count_label = widgets.Label(value="")
distance_label = widgets.Label(value="")
travel_time_taken_label = widgets.Label(value="")
```

2.5 Pathfinding Algorithms

This section implements the following algorithms:

- A*
- A* traveltime
- Djikstra
- BFS traveltime

2.5.1 Breadth-First Search (BFS) Algorithm

The **Breadth-First Search (BFS) algorithm** systematically explores the vertices of a graph by expanding all vertices at the present depth level before progressing to vertices at the next depth level. The algorithm operates as follows:

Initialization: - Verify the presence of the start vertex s and the goal vertex g in the graph G.

- Initialize a queue Q with the start vertex s. - Create a set V_{visited} to track visited vertices. - Maintain a dictionary P to record the predecessor of each vertex for path reconstruction.

Exploration: - Dequeue a vertex v from Q. - For each neighbor u of v that has not been visited: - Mark u as visited and enqueue u to Q. - Set $P[u] = v$.

Pathfinding: - The search terminates when the goal vertex g is dequeued. - Reconstruct the path by backtracking from g to s using the predecessor dictionary P.

Visualization: - If visualization is enabled, mark each visited vertex on the map. - Cluster markers in groups of 100 for efficient rendering.

Completion: - If the goal vertex g is found, return the reconstructed path. - If g is not found, return the list of all visited vertices.

2.5.2 Key Characteristics:

Breadth-Wise Exploration: BFS ensures that all vertices at the current depth d are explored before moving to depth $d + 1$.

Guaranteed Shortest Path: BFS guarantees finding the shortest path in an unweighted graph, as it explores all possible paths level by level.

Time Complexity: The time complexity of BFS is $O(V + E)$, where V is the number of vertices and E is the number of edges in the graph.

[4]:
```
def bfs(G, start, goal=None):
    if start not in G:
        raise ValueError(f"Start node {start} not in the graph.")
    if goal is not None and goal not in G:
        raise ValueError(f"Goal node {goal} not in the graph.")

    queue = deque([start])
    visited = set([start])
    parent = {start: None}
    g_costs = {start: 0}
    time_taken = {start: 0}
    circles = []

    while queue:
        current_node = queue.popleft()
        path = []  # Path is reconstructed once we find the goal node

        if show_nodes.value:
            circle = Circle(location=(G.nodes[current_node]["y"], G.
↪nodes[current_node]["x"]),
                            radius=1,
                            color=node_color.value,
                            fill_color=node_color.value)
            circles.append(circle)
```

```python
        if len(circles) > 100:
            marker_cluster = MarkerCluster(markers=circles)
            m.add_layer(marker_cluster)
            circles.clear()
            print("Marker added")

        # If we reached the goal, return the path
        if current_node == goal:
            # Reconstruct the path from goal to start
            while current_node is not None:
                path.append(current_node)
                current_node = parent[current_node]
            path.reverse()
            marker_cluster = MarkerCluster(markers=circles)
            m.add_layer(marker_cluster)
            print("Found solution: ", path)
            return path, g_costs, time_taken

        # Explore neighbors
        for neighbor in G.neighbors(current_node):
            if neighbor not in visited:
                visited.add(neighbor)
                parent[neighbor] = current_node
                queue.append(neighbor)
                # Set g_costs and time_taken for BFS, even though BFS doesn't␣
↪calculate these.
                g_costs[neighbor] = g_costs[current_node] + 1
                time_taken[neighbor] = 0  # Time is not used in BFS

    if goal is not None:
        return None
    return list(visited), g_costs, time_taken
```

2.5.3 Dijkstra's Algorithm for Shortest Pathfinding

Dijkstra's Algorithm is a fundamental algorithm in graph theory, designed to determine the shortest path between nodes in a weighted graph. It is particularly applicable in scenarios such as road networks, where edges have varying weights representing distances, travel times, or costs.

Algorithm Description Dijkstra's Algorithm operates by maintaining a priority queue, typically implemented as a min-heap, to ensure that the node with the lowest current cost is expanded first. The algorithm proceeds as follows:

1. **Initialization**:
   - Set the distance to the start node s to zero: $d(s) = 0$.
   - Set the distance to all other nodes to infinity: $d(v) = \infty$ for all $v \neq s$.
   - Initialize a priority queue Q containing all nodes, prioritized by their current distance.
2. **Main Loop**:

- Extract the node u with the smallest distance $d(u)$ from Q.
- For each neighbor v of u:
  - Calculate the tentative distance through u: $d_{\text{tentative}}(v) = d(u) + w(u, v)$, where $w(u, v)$ is the weight of the edge from u to v.
  - If $d_{\text{tentative}}(v) < d(v)$:
    * Update $d(v)$ to $d_{\text{tentative}}(v)$.
    * Record u as the predecessor of v for path reconstruction.

3. **Termination**:
   - The algorithm terminates when all nodes have been processed, and the shortest path distances from s to all other nodes are determined.

Mathematical Formulation The algorithm guarantees finding the shortest path in a weighted graph by iteratively selecting the node with the minimum tentative distance and updating the distances of its neighbors. The key steps can be summarized as:

$$d(v) = \min\left(d(v), d(u) + w(u, v)\right)$$

where $d(v)$ is the shortest known distance to node v, $d(u)$ is the shortest known distance to node u, and $w(u, v)$ is the weight of the edge from u to v.

Performance and Complexity Dijkstra's Algorithm has a time complexity of $O((V+E)\log V)$, where V is the number of vertices and E is the number of edges. This complexity arises from the need to update and extract the minimum distance nodes from the priority queue efficiently.

Visualization and Applications Visualization of Dijkstra's Algorithm can illustrate the exploration of nodes and the construction of the shortest path. It can also display metrics such as total path distance and travel time, depending on the edge weights used. The algorithm is widely used in real-world applications, including GPS navigation systems, network routing, and urban planning, where optimal pathfinding is crucial.

By leveraging the priority queue and edge weights, Dijkstra's Algorithm ensures that the path with the minimum total cost is selected, making it a robust and reliable method for shortest pathfinding in weighted graphs.

2.5.4 A* Algorithm for Shortest Pathfinding

The **A* (A-star) Algorithm** enhances Dijkstra's algorithm by incorporating a heuristic function that estimates the remaining distance to the goal, making it more efficient for many practical applications, such as navigation and AI pathfinding.

Key Features of the Algorithm: The A* Algorithm improves upon Dijkstra's algorithm by using a heuristic function to estimate the remaining travel time to the goal. This approach makes it more efficient for practical applications, such as navigation and AI pathfinding, where travel time is a critical factor.

A* uses the Haversine formula as its heuristic to estimate the cost from the current node to the goal. This choice is particularly suited for geographic distance calculations on a spherical surface.

The total cost in A* is calculated as $f(n) = g(n) + h(n)$, where $g(n)$ represents the actual travel time from the start to the current node, and $h(n)$ is the heuristic estimate of the travel time from the current node to the goal. By combining these factors, A* explores fewer nodes compared to Dijkstra, resulting in faster performance in many cases.

A* guarantees finding the shortest path if the heuristic is admissible, meaning it never overestimates the true travel time to the goal. With an appropriate heuristic, A* will yield the same result as Dijkstra in optimal scenarios.

Comparison with Dijkstra:

- **Efficiency**: A* is generally more efficient than Dijkstra because the heuristic function directs the search towards the goal, reducing unnecessary exploration of nodes, especially in large graphs or grids. In contrast, Dijkstra explores uniformly in all directions, which can lead to more exhaustive searches.
- **Computational Overhead**: While A* incurs additional overhead from calculating the heuristic at each step, this is often outweighed by the significant reduction in the number of nodes explored.

Use Cases:

- In graphs where Dijkstra would take too long computationally, A* is a better choice.

2.5.5 Traveltime Variants

In addition to the standard versions of Dijkstra and A*, the project also includes variants that account for **travel time** instead of the physical length of roads. This allows the algorithms to find the fastest route, rather than the shortest one, making them more suitable for real-world street navigation where traffic conditions, road speed limits, and other factors impact travel time. These variants are particularly beneficial in applications like GPS navigation, where minimizing travel time is often more important than minimizing distance.

[5]:
```
import numpy as np

def astar_fast(G,start,goal,travel_time=False,djikstra=False):
    print(travel_time)
    global show_nodes
    print("Starting A* algorithm, please wait")
    def heuristic(node,target):
        to = G.nodes[target]["y"],G.nodes[target]["x"]
        fr = G.nodes[node]["y"],G.nodes[node]["x"]
        if not djikstra:
            return haversine(to,fr,unit='m')
        else:
            return 0
    open_set = []
    heapq.heappush(open_set, (0, start, [start]))
    g_costs = {start: 0}
    dists = {start:0}
```

```
    time_taken = {start:0}
    circles=[]
    while open_set:
        _, current_node, path = heapq.heappop(open_set)
        if show_nodes.value:
            circle = Circle(location = (graph.nodes[current_node]["y"], graph.
↪nodes[current_node]["x"]),
                radius = 1,
                color = node_color.value,
                fill_color = node_color.value)
            circles.append(circle)
        if len(circles)>100:
            marker_cluster = MarkerCluster(markers=circles)
            m.add_layer(marker_cluster)
            circles.clear()
            print("marker added")
        # If we reached the goal, return the path
        if current_node == goal:
            marker_cluster = MarkerCluster(markers=circles)
            m.add_layer(marker_cluster)
            print("Fount solution: ",path)
            return path,(g_costs if not travel_time else dists),time_taken
        # Explore neighbors
        for neighbor in G.adj[current_node]:
            # Get all edges between current_node and neighbor
            for key, edge_attr in G[current_node][neighbor].items():
                lane_speedup = 0.5
                if 'lanes' in edge_attr:
                    print(edge_attr['lanes'])
                    if type(edge_attr['lanes'] == type([])):
                        lane_speedup = max([int(x) for x in edge_attr['lanes']])

                x = float(edge_attr['travel_time']/lane_speedup)
                if travel_time:
                    tentative_g_cost = g_costs[current_node] + x
                    if neighbor not in dists or tentative_g_cost <␣
↪dists[neighbor]:
                        dists[neighbor]= dists[current_node] +␣
↪(edge_attr['length'])
                else:
                    tentative_g_cost = g_costs[current_node] +␣
↪(edge_attr['length'])

                if neighbor not in g_costs or tentative_g_cost <␣
↪g_costs[neighbor]:
                    g_costs[neighbor] = tentative_g_cost
                    f_cost = tentative_g_cost + (heuristic(neighbor,goal))
```

```
                    heapq.heappush(open_set, (f_cost, neighbor, path +
↪[neighbor]))

                time_from_last = time_taken[current_node] +
↪(edge_attr['travel_time']/lane_speedup)
                if neighbor not in time_taken or time_from_last <
↪time_taken[neighbor]:
                    time_taken[neighbor] = (time_taken[current_node] + x)

    return None
```

2.6 Usage of GeoPandas for Adding Layers visualising the path

In the `draw_path` function, **GeoPandas** is employed to visualize the computed path on the map by performing the following steps:

1. **Path Construction**:
   - The function computes the path using different algorithms (e.g., A*, Dijkstra, BFS) and extracts the geometry of the path segments between nodes.
2. **Geometry Extraction**:
   - For each segment of the path, the function checks if geometry data is present in the graph's edge attributes.
   - If geometry data exists, it is directly used; otherwise, the function creates a `LineString` object using the coordinates of the nodes.
3. **GeoDataFrame Creation**:
   - A `GeoDataFrame` is created from the list of path segments, which includes line geometries representing the path on the map.
4. **Layer Addition**:
   - A `GeoData` layer is generated from the `GeoDataFrame` with a specified style (color and weight) to represent the path.
   - This layer is then added to the map using `m.add_layer()`, allowing visualization of the computed path with the desired styling.
5. **Memory Management**:
   - After adding the layer, the `path` variable is deleted to free up memory.

[6]:
```
def draw_path(G,source,target,algo):
    start = timeit.default_timer()
    if source == target:
        alg = {'distances': {source: 0}, 'prev_vertices': {source: source},
↪'count': 0}

    if algo=='astar':
        path = (astar_fast(G,source,target))
    elif algo == 'astar (traveltime)':
        path = (astar_fast(G,source,target,travel_time=True))
    elif algo == 'djikstra':
        path = (astar_fast(G,source,target,djikstra=True))
```

```
    elif algo == 'djikstra (traveltime)':
        path = (astar_fast(G,source,target,travel_time=True,djikstra=True))
    elif algo == 'bfs':
        path = (bfs(G,source,target))
    print(path)
    path,distance,time =path[0],path[1][target],path[2][target]

    end = (timeit.default_timer() - start) * 1000

    edges = []

    for i in range(len(path)-1):
        if 'geometry' in G[path[i]][path[i+1]][0]: # im sorry to my future self␣
↪when he reads this
            edges.append(G[path[i]][path[i+1]][0]['geometry'])
        else:
            # next 2 lines are chatgpt magic...
            x = [path[i], path[i+1]]
            edges.append(LineString(nodes.loc[x].geometry.values))

    path = gpd.GeoDataFrame(edges,columns=['geometry'])
    path_layer = GeoData(geo_dataframe=path,style={'color': path_color.value,␣
↪'weight': 4})
    m.add_layer(path_layer)

    del path
    return end, 0,distance,time
```

The `assign_closest_node` function assigns the marker to the closest node on the actual map

[7]:
```
def assign_closest_node(marker):
    nearest_node = ox.nearest_nodes(graph,marker.location[1],marker.
↪location[0],return_dist=False)
    marker.nearest_node = nearest_node
    return
```

[8]:
```
def fix_location(event):
    global dropdown
    marker = event['owner']
    assign_closest_node(marker)
    try:
        alg = dropdown.value
    except:
        alg = 'astar'
    marker.location = graph.nodes[marker.nearest_node]["y"], graph.nodes[marker.
↪nearest_node]["x"]
    time_label.value = "changed location to nearest valid node"
```

```
    count_label.value = ""
    distance_label.value = ""
    travel_time_taken_label = ""
```

2.6.1 loadmap Function Process

The `loadmap` function handles the dynamic loading and visualization of map data. It begins by displaying a loading progress bar to indicate data retrieval. The function then checks if a graph is already loaded and clears existing data if necessary. Depending on user input, it either loads a pre-saved graph or fetches new data from OpenStreetMap, enhancing it with edge speeds and travel times for accurate pathfinding.

Next, it converts the graph data into GeoDataFrames for nodes and edges, initializes a map centered on the first node, and sets up interactive elements including markers for the start and end points. The function adds a dropdown menu for selecting pathfinding algorithms and buttons for visualizing the path and clearing the map.

Pathfinding results are computed and displayed when the user clicks the visualize button, showing statistics like elapsed time, nodes traversed, distance, and travel time. The clear button allows users to reset the map view. If an error occurs, the function resets all components and informs the user of any issues.

Overall, the `loadmap` function provides an interactive map experience with flexible pathfinding options and visual feedback.

[9]:
```
def loadmap(wdgt):

    global␣
↪graph,nodes,edges,center,m,from_marker,to_marker,dropdown,show_nodes,show_node_control,trav
    loading = widgets.IntProgress(value=10,min=0,max=10,description="Loading␣
↪data",
                bar_style='', # 'success', 'info', 'warning', 'danger' or ''
                style={'bar_color': 'green'},
                orientation='horizontal'
                )
    box.children = [box.children[0], loading]

    value = wdgt['new']

    try:
        if graph is not None:
            del graph
            del nodes
            del edges
            del center
            del m
            del from_marker
            del to_marker
            # print(value.lower())
```

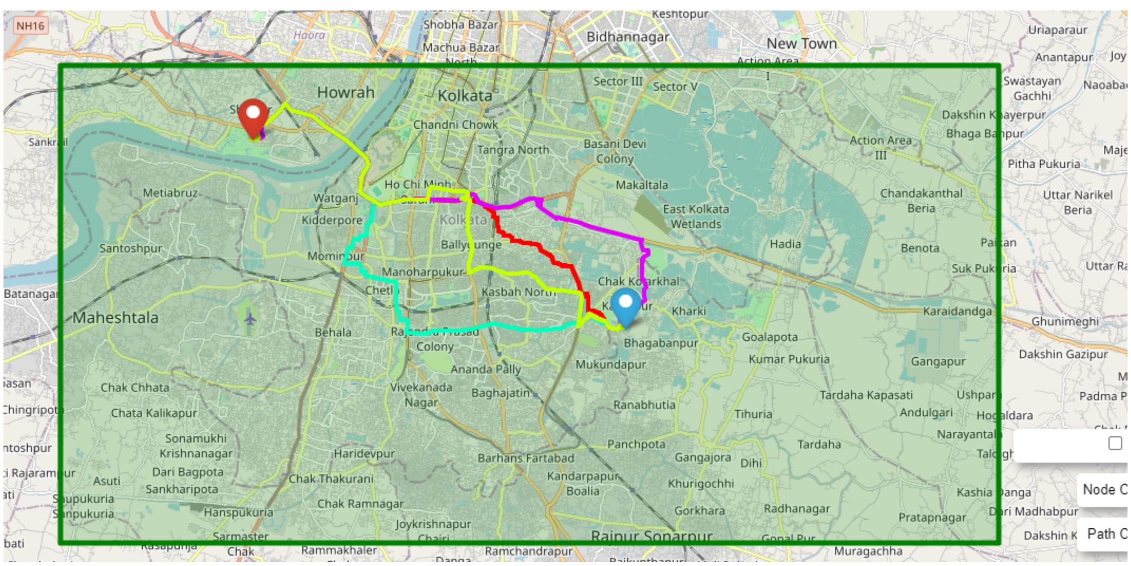
```
        if (value in preloaded):
            graph = pickle.load(open(preloaded[value], "rb"))

        else:
            graph = ox.graph_from_address(value, network_type =␣
↪'drive',dist=10000)

        graph  = ox.add_edge_speeds(graph,hwy_speeds={
    'motorway':80,
    'living_street':40,
    'road':10,
    'primary':80,
    'secondary':15,
    'residential':10,
    'unclassified':10,
    'tertiary':10,
    'trunk':80
    },fallback=30
                              )
        graph = ox.add_edge_travel_times(graph)

        nodes, edges = ox.graph_to_gdfs(graph)



        center = graph.nodes[nodes.index[0]]["y"], graph.nodes[nodes.
↪index[0]]["x"]

        m = Map(center = center,
                basemap = basemaps.OpenStreetMap.Mapnik,
                zoom = 18,
                max_zoom = 18,
                min_zoom = 8,
                scroll_wheel_zoom = True,
                layout = mapLayout)

        print(type(m))

        from_marker = Marker(location=center, icon=from_marker_style)
        to_marker = Marker(location=center, icon=to_marker_style)


        from_marker.observe(lambda event: fix_location(event), 'location')
        to_marker.observe(lambda event: fix_location(event), 'location')

        assign_closest_node(from_marker)
        assign_closest_node(to_marker)
```

```
    m.add_layer(from_marker)
    m.add_layer(to_marker)



    dropdown = widgets.Dropdown(
                options=['astar','astar (traveltime)',␣
↪'bfs','djikstra','djikstra (traveltime)'],
                value="astar",
                description='Algorithm:',
                tooltip='Select algorithm to visualize',
                disabled=False,
                )

    dropdown_control = WidgetControl(widget=dropdown, position='topright')

    dropdown_control = WidgetControl(widget=dropdown, position='topright')

    layout = widgets.Layout(width='100px', height='30px')



    button = widgets.Button(
        description='Visualize',
        disabled=False,
        button_style='', # 'success', 'info', 'warning', 'danger' or ''
        tooltip='Click to visualize selected pathfinding algorithm',
        icon='play', # (FontAwesome names without `fa-` prefix)
        layout = layout
    )

    minx,miny,maxx,maxy = nodes.total_bounds
    # print((miny,minx),(mayx,maxy))
    bounding_box = Rectangle(
                bounds=((miny,minx),(maxy,maxx)),
                color = 'green',
    )

    m.add_layer(bounding_box)
    def button_action(arg):
        x = draw_path(graph,from_marker.nearest_node,to_marker.
↪nearest_node,dropdown.value)
        if x is not None:
            time_label.value = "elapsed time: " + str(x[0]) + ' ms'
            count_label.value = "nodes traversed: " + str(x[1])
            distance_label.value = "total path distance: " + str(x[2]/1000)␣
↪+ " km"
```

```
                travel_time_taken_label.value = f"{x[3]/60} minutes"
            else:
                time_label.value = "No path found"
                count_label.value = ""
                distance_label.value = ""

        button.on_click(button_action)
        button_control = WidgetControl(widget=button, position='topright')

        clear = widgets.Button(
            description='Clear Map',
            disabled=False,
            button_style='', # 'success', 'info', 'warning', 'danger' or ''
            tooltip='Clear nodes and path from map',
            icon='trash',
            layout = layout
        )

        def clear_action(arg):
            m.clear_layers()
            m.add_layer(from_marker)
            m.add_layer(to_marker)
            m.add_layer(base)
            m.add_layer(bounding_box)



        clear.on_click(clear_action)
        clear_control = WidgetControl(widget=clear, position='topright')

        m.add_control(dropdown_control)
        m.add_control(button_control)
        m.add_control(clear_control)
        m.add_control(path_control)
        m.add_control(node_control)
        m.add_control(show_node_control)

        box.children = [box.children[0], widgets.Label(value="Total Nodes: " +␣
↪str(len(nodes))),
                        widgets.Label(value="Total Edges: " + str(len(edges))),
                        m,time_label, count_label,␣
↪distance_label,travel_time_taken_label]
        # ox.plot_graph(graph, show=False,␣
↪close=False,edge_color="#d4af37",node_size=5,node_color="#f9f1f1")
        edges.explore()
    except EOFError:
        # print(e)
```

```
        graph = nodes = edges = center = m = from_marker = to_marker = dropdown = None
        box.children = [box.children[0], widgets.Label(value="Couldn't find location try again (e.g. Monaco)")]

regionInput = widgets.Text(
                value = 'Address:',
                placeholder = 'Type a Location',
                description = 'Location:',
                disabled = False,
                )


regionInput.continuous_update=False

regionInput.observe(loadmap,'value')

box_layout = widgets.Layout(display='flex',
                flex_flow='column',
                width='100%',
                height='100%')

box = widgets.HBox([regionInput], layout=box_layout)
```

2.6.2 Example output (for PDF files)



- Red (djikstra / A*)
- Lime green (djikstra traveltime)
- Cyan (A* traveltime)
- Pink (BFS)

[10]:
```
display(box)
```

```
HBox(children=(Text(value='Address:', continuous_update=False,␣
↪description='Location:', placeholder='Type a Lo…
```

3 The results:

Both Standard A* and Dijkstra's Algorithms equal performance. In the cities tested, both algorithms generally converge on the same paths; however, A* consistently outperforms Dijkstra in terms of computational speed, owing to its heuristic-driven approach.

When evaluating pathfinding with travel time as the cost metric, notable differences emerge between A* and Dijkstra. For shorter distances, the discrepancy in travel time between the two algorithms ranges from 10% to 30%. This variation arises because, although both algorithms aim to minimize travel time, their methods of achieving this can lead to divergent paths. For longer distances, the differences become less predictable and are significantly influenced by the specific layout of the city's road network.

An analysis of the algorithms' behavior reveals that Dijkstra's Algorithm, when optimized for travel time, tends to favor larger roads with higher lane counts and generally avoids residential streets. This preference is due to its method of evaluating paths based on total travel time, which often favors major roads over smaller, potentially slower routes.

In contrast, A* Algorithm, despite its heuristic advantages, sometimes selects suboptimal routes when travel time is considered. It can be misguided by heuristics that favor initially perceived faster routes, which may lead into slower residential areas if the heuristic mistakenly prioritizes these over more efficient routes. This can occur if the heuristic eliminates what appears to be slower paths initially, only to find that these paths are actually faster in the overall context.

Future enhancements could involve integrating real-world speed limits and other detailed data to refine pathfinding accuracy. However, acquiring such comprehensive data is currently beyond the scope of this project.