### Introduction

The program is divided into four main parts: create the city graph, define five search function, visualize the map, and call the search function do the calculation.

First of all, generate a 100\*100 list, which like the world\_map, and then randomly select 26 pairs of x-axis and y-axis (check to make sure they are all different), then assign the city name from A to Z to the pairs. Store the location into a dictionary.

Secondly, use the location dictionary to calculate the distance between cities for each city, and then select the closest four neighbours (not include the city itself) for each city and store them in a ordered dictionary, which will be the city graph. Also check the graph to make sure that the edge is bi-directional. In my case, the neighbour cities stored in the graph are sorted based on the closest distance. Therefore, the final city graph looks like:

```
OrderedDict([('A', ['V', 'G', 'K', 'F', 'N']), ('B', ['W', 'F', 'R', 'L', 'H',
K']), ('C', ['T', 'O', 'M', 'U', 'D', 'J']), ('D', ['J', 'Z',
        'X', 'R', 'L']), ('F', ['R', 'K', 'B', 'Q', 'A',
                                                                              'G']), ('G', ['Q',
                                      'W', 'B', 'R']), ('I', ['Z', 'S', 'J',
             'V']), ('H', ['L',
                              'C', 'S']), ('K', ['F', 'Q', 'R',
                      Ί',
                                                                              'B',
                                                            'X',
            'B', 'R', 'E']), ('M', ['T', 'P',
                                                                    '0', 'C',
                                                                                  'N',
                                                                                        'Y']), ('N', ['V'
         'A', 'M']), ('O', ['C', 'T', 'M', 'P',
                                                                 'Y']), ('P', ['Y',
  ('Q', ['G', 'K', 'F', 'R']), ('R', ['F', 'K', 'B', 'W', 'E', 'H', 'L', 'Q']), 'S', ['I', 'Z', 'U', 'J']), ('T', ['C', '0', 'M', 'X', 'P', 'U', 'Y']), ('U', [E', 'C', 'I', 'T', 'S', 'Z']), ('V', ['A', 'N', 'X', 'G']), ('W', ['B', 'L', 'H', 'R']), ('X', ['M', 'N', 'T', 'E', 'V']), ('Y', ['P', 'M', '0', 'T']), ('Z', [
('S', ['I', 'Z', 'U',
'I', 'S', 'J', 'U', 'D'])])
```

(The closest neighbours of A will be V, then G then K then F, then N. etc. The reason why A has 5 neighbours is because N is not the top four close cities of A, but A is the top four of N. Thus, because of the bi-directional edges, N was added to A's neighbours)

Thirdly, write a for loop to call those functions (because we want to generate 100 instance). In the for loop, call the function to generate the world map, then call the function to generate the city graph. Now randomly generate two city names from A to Z

(make sure they are not same) as the start state and goal state, for example, start\_state = 'A', goal state = 'C'.

Fourthly, define the search function and implement the search algorithm. Details will be introduced in the implementation overview section.

Fifthly, call the search function, given the start state, goal state and city graph as the basic parameters. For different search algorithm, the input parameter might be different. Search function will return the path, the number of explored cities (which will be the time complexity) and also the maximum nodes generated (which will be the space complexity). Calculate the total space complexity, time complexity, running time, path length and number of solved problem.

Sixthly, after the for loop, calculate the average of the above statistics.

### **Experimental Results**

Firstly, I want to answer the questions in the assignment requirement.

Q1: The way how I formulate this problem as a search problem is as what I mentioned in the previous section. I create a city graph, and randomly select two city names, and given start city name, goal city name, and also the city graph as the parameters when I call the search function. The state space is presented by the city name. The successor-function is like the neighbours which will be visited next. This can be get through the city graph, like city\_graph[city\_name], and this will return all the neighbours of the current city, which will be the successors.

**Q2:** After generate 100 instance graph and calculate the branches, the average branches is 104. The way to count the branches is done by the visualization method. Every time draw an edge, increase the count of branches.

Q3: Examples of calling breadth first search (bfs), depth first search (dfs) and iterative deepening search (ids, consider the running time of the iterative deepening search, set the depth to 10) are as follow:

```
#run bfs
city_graph = create_graph(city_location)
bfs start time = time.time()
bfs_result = bfs(start_state, goal_state, city_graph)
bfs end time = time.time()
bfs running time = bfs running time + (bfs end time - bfs start time)
bfs path = None
if bfs result is not None:
   bfs solved = bfs solved + 1
   bfs path = bfs result[0]
   bfs_path_len = bfs_path_len + len(bfs_path)
   bfs time complexity = bfs time complexity + int(bfs result[1])
   bfs_space_complexity = bfs_space_complexity + int(bfs_result[2])
print 'bfs_path:', bfs_path
#run dfs
city graph = create graph(city location)
dfs start time = time.time()
dfs_result = dfs(start_state, goal_state, city_graph)
dfs end time = time.time()
dfs running time = dfs running time + (dfs end time - dfs start time)
dfs_path = None
if dfs result is not None:
   dfs solved = dfs solved + 1
   dfs_path = dfs_result[0]
   dfs_path_len = dfs_path_len + len(dfs_path)
   dfs time complexity = dfs time complexity + dfs result[1]
   dfs_space_complexity = dfs_space_complexity + dfs_result[2]
print 'dfs_path:', dfs_path
#run ids
city_graph = create_graph(city_location)
ids start time = time.time()
ids_result = ids(start_state, goal_state, city_graph)
ids_end_time = time.time()
ids running time = ids running time + (ids end time - ids start time)
ids_path = None
if ids result is not None:
   ids solved = ids solved + 1
   ids path = ids result[0]
   ids_path_len = ids_path_len + len(ids_path)
   ids_time_complexity = ids_time_complexity + ids_result[1]
   ids_space_complexity = ids_space_complexity + ids_result[1]
print 'ids_path:', ids_path
```

#### Result looks like:

```
start_state: M
goal_state: S
bfs_path: ['M', 'N', 'S']
dfs_path: ['M', '0', 'Y', 'S']
ids_path: ['M', 'N', 'S']
OrderedDict([('A', ['X', 'G', 'P', 'F']), ('B', ['E', 'R', 'Z', 'Q']), ('C', ['J', 'L', 'K', 'W', 'V']), ('D', ['G', 'M', 'X', 'H', 'F']), ('E', ['R', 'B', 'P', 'U']), ('F', ['X', 'G', 'A', 'D']), ('G', ['X', 'D', 'A', 'P', 'F']), ('H', ['M', '0', 'D', 'I']), ('I', ['N', 'M', '0', 'U', 'H']), ('J', ['C', 'V', 'S', 'L', 'W']), ('K', ['T', 'Q', 'Z', 'C', 'L', 'W']), ('L', ['W', 'C', 'J', 'K']), ('M', 'I', 'N', 'H', 'Y']), ('P', ['R', 'U', 'E', 'A', 'G']), ('Q', ['Z', 'T', 'K', 'U', 'B']), ('R', ['E', 'P', 'U', 'Z', 'B']), ('S', ['V', 'Y', 'J', 'N']), ('T', ['Z', 'Q', 'K', 'U']), ('W', ['Z', 'T', 'K']), ('X', ['G', 'A', 'F', 'D']), ('Y', ['S', 'V', 'O', 'N']), ('Z', ['Q', 'U', 'T', 'K', 'B', 'R'])])
```

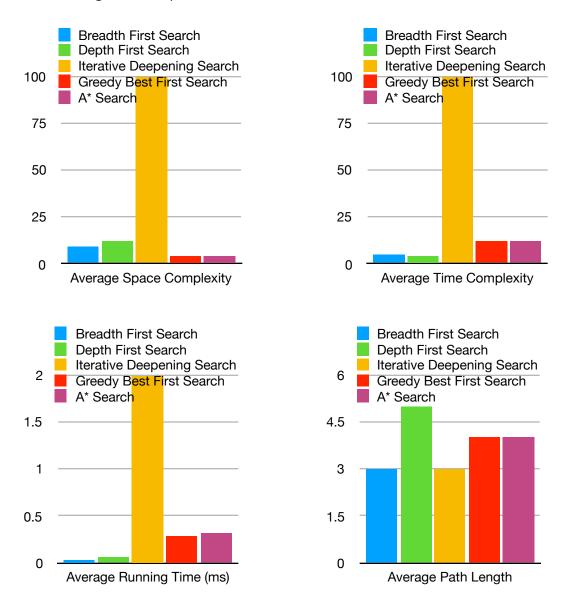
Q4, Q6: The results are based on the same 100 graph, which means every time generate a graph, run these five search algorithm and record the result.

Search Alg.	Average Space Complexity	Average Time Complexity	Average Running Time (s)	Average Path Length	Problems Solved
Breadth First (bfs )	9 O(bd+1)	5 O(bd+1)	2.54E-05	3	97
Depth First (dfs)	12 O(bm)	4 O(b <sup>m</sup> )	5.9E-05	5	97
Iterative Deepening (ids)	601 O(bm)	601 O(b <sup>m</sup> )	0.034	3	97
Greedy Best First (bestfs)	4 O(b <sup>m</sup> )	12 O(b <sup>m</sup> )	0.00028	4	97
A*	4 O(b <sup>m</sup> )	12 O(b <sup>m</sup> )	0.00031	4	97

Here I will do the experimental result analysis:

Based on the average space complexity, we could see that ids has the highest amount, which is what we could imagine. Because it is doing the recursive visit according to the depth, it will use more memory than others and also cause a longer running time (especially when it has no solution). For greedy best first search and A\* search, because they do a selection before select the neighbours, so they will store less useless cities and also because of the selection, it will take a little bit longer running time. The time complexity is vary depends on the situation, but overall, ids visit the most amount of nodes. For the average path length, we could see that dfs has a longer length and that because dfs will not always return a optimal path. Whereas bfs and ids

will return the shortest path, while, greedy best first search (not optimal) and A\* is more rely on the distance cost. Because all search algorithm are running on the same graph every time, so the solved problems is equal in this sample. The bar graph could also show the same thing: (for a better view, set a upper bound for the value, but know that ids has a large amount)



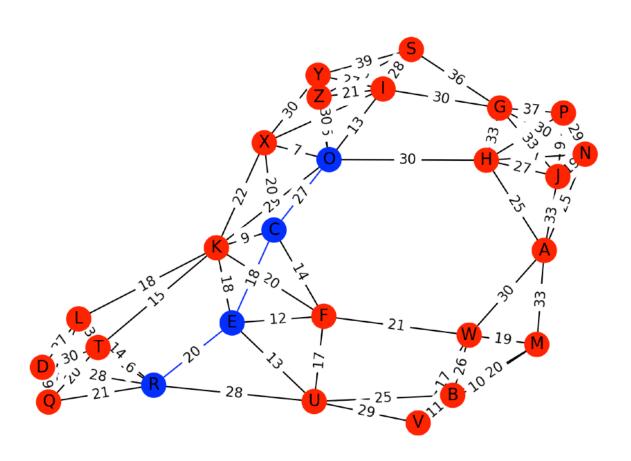
**Q5:** (he) straight-line Euclidean distance is the direct distance between the current state to the goal state. (h0) means that the start state is the goal state. (hm) Manhattan distance measures the distance in the two dimension coordinates and count the move steps. In the greedy best-first search, the heuristic function takes the (he) estimated

cost to the goal state, which means that the next explored node should has the shortest (he) straight-line distance to the goal state. But the return path might not be optimal. While in the A\* search, the heuristic takes both the real cost to the current, and the estimated cost to the goal state. For example, if currently at city C, then A\* will search if there is a less cost path to get C, if there is one, then get rid of the current one, choose the less cost one. Thus, the return path is optimal. Considering the heuristics is because want to get a optimal path.

When h(m) > h(e) for all n nodes, then h(m) dominates h(e) better for search.

Q7: Visualizes the cities and path and show examples of how it would work.

After running the breadth first search, call the method draw\_graph(city\_graph, city\_location, bfs\_path) and then it will show a graph looks like this:



Where blue nodes and the blue edges is the path.

## Implementation Overview

The program is implemented using python based on the sudo code from textbook and also the graph search algorithm from aima GitHub account. As mentioned before, the program is basically divided into four parts: create the city map, define the search algorithm, visualize the city map and call the search function do the calculation. Now I am going to introduce each function in my program.

For the first part, create the city map, there are three function I wrote:

**create\_map()**: used to generate a 100\*100 list and then randomly assign 26 cities' location. Return a list of city location.

dist\_cost(listone, listtwo): used to calculate the distance between two cities. Return an int distance value.

**create\_graph(city\_location):** used to create the city map. Return an ordered dictionary which is the city graph.

For the second part, define search function, I will introduce each search method and some variables I used in all method.

#### Variables:

frontier: list that stores the neighbours of the start state. It is a queue in the breadth first search function, but it is a stack in the depth first search function. I define it clearly in the code.

**frontier\_size:** This is used to track the space complexity. It is the maximum size of the queue or the stack.

explored: list of all the nodes have been visited

parent: dictionary that used to track where the node comes from

### **Function:**

get\_path(parent, start, end): This is a general method of getting the path by given the parent list and the start, end state. Return a list contains the path.

bfs(start\_state, goal\_state, city\_graph): This is the method of breadth first search algorithm. When the frontier is not empty, get the first-in one and check if it is the goal state. If not, then check each of its child (neighbour), if not been visited not in the

frontier, check if it is the goal, if not then add to the frontier, else return. Return the path, total number of nodes been visited, maximum size of the queue or none.

dfs(start\_state, goal\_state, city\_graph): This is the method of depth first search algorithm. Same idea as the previous one, instead frontier here is a stack, and always get the last-in one to check. Return the path, total number of nodes been visited, maximum size of the stack or none.

ids(start\_state, goal\_state, city\_graph): This is the method of iterative deepening search algorithm. Set a depth (consider the running time, set it to 10), and call the depth\_limited\_search and return the result from there or none.

depth\_limited\_search(start\_state, goal\_state, city\_graph, limit): Inside this method, define a recursive method to search based on the limit. Because it is recursive, to calculate this space complexity, I use the (node in current depth) times depth to present. Return the path, total number of nodes been visited, space complexity or none.

best\_first\_search(start\_state, goal\_state, city\_graph, f): f here is the list of the straight line distance from each node to the goal state. In the method, frontier is the priority queue. The priority of each neighbour city is assigned using the integer distance to the goal state (example frontier = [[55,'A'],[27, 'B'],[60, 'C']]). Because the neighbour cities are already sorted based on the distance (mentioned in the very beginning, this is the way I create the graph), so the running result is almost the same as the A\* search. Return the path, total number of nodes been visited, maximum size of the queue or none.

cost(goal\_state, city\_location): Calculate the distance from each node to the distance.

**A\_star\_search(start\_state, goal\_state, city\_graph, city\_location, h):** h plays the same role as the f in the greedy best first search. I add g which is a dictionary contains the real cost from start node to the current node. Return the path, total number of nodes been visited, maximum size of the gueue or none.

Third part is to visualize the graph. I import the matplotlib.pyplot and networkx.

draw\_graph(city\_graph, city\_location, path): Create an empty graph and add the node and edges to it. Draw it with different colour and value.

Last part is just the for loop to call the above function. Call create\_map() and create\_graph() to get the city graph and then randomly select two city names. Call each search function to calculate the statistics. After the for loop, calculate the average statistics for each search function.

# **Code Listing**

```
import re
import sys
import random
import math
import collections
import Queue
import matplotlib.pyplot as plt
import networkx as nx
from datetime import datetime
import timeit
import time
#randomly create the world map with 26 cities
def create map():
   #global world map
   world map = [[0 \text{ for } x \text{ in range}(100)] \text{ for } y \text{ in range}(100)] \#range(100): 0-99
   city list = collections.OrderedDict()
   for i in range(26): #0-25
      x = random.randint (0,99) #0-99
      y = random.randint (0,99)
      #while world_map[x][y] != 0:
      while world map[x][y] is not 0:
         x = random.randint (0.99)
         y = random.randint (0,99)
      if world map[x][y] is 0:
         city name = chr(ord('A') + i)
         world_map[x][y] = city_name
         city_list[city_name] = [x,y]
         #print(city_list)
   return city list
#calculate the closest four neighbours for each city
def create graph(city location):
   graph = collections.OrderedDict()
```

```
for i in range(26):
      city name = chr(ord('A') + i)
      all neighbor = {}
      for j in range(26):
         cmped city name = chr(ord('A') + i)
         dist = dist_cost(city_location[city_name], city_location[cmped_city_name])
         if dist!= 0:
             all neighbor[cmped city name] = dist
      # sort all neighbors based on distance
      sorted neighbor = sorted(all neighbor.items(), key = lambda x:x[1])
      close_neighbor = [] # the four closest neighbors
      for i in range(4):
         close neighbor.append(sorted neighbor[i][0])
      graph[city name] = close neighbor
   #add bi-direction neighbor, if A:[B,C,D,T], but B:[M,N,Q,E], need add A to B's neighbor list
   for i in range(26):
      city name = chr(ord('A') + i)
      for j in range(26):
         cmped\_city\_name = chr(ord('A') + j)
         if city name in graph[cmped city name]:
             if cmped_city_name not in graph[city_name]:
                graph[city name].append(cmped city name)
   return graph
def dist cost(listone, listtwo):
   x dist = listone[0]-listtwo[0]
   y dist = listone[1]-listtwo[1]
   square dist = math.pow(x dist,2) + math.pow(y dist,2)
   distance = math.sqrt(square dist)
   new distance = int(distance)
   return new distance
#general method of getting the path
def get_path(parent, start, end):
   child = end
   path = [end]
# print 'parent:', parent
   if start in parent:
      del parent[start]
   if child in parent:
      while parent[child]:
         if parent[child] in path:
             break
         path.append(parent[child])
         child = parent[child]
         if child not in parent:
             break
         # avoid the case 'K': 'I', 'I': 'K', while loop will be infinite
         child parent = parent[child]
         if child parent in parent:
```

```
if parent[child_parent] == child:
               if child parent not in path:
                  path.append(child parent)
               break
   if start != path[-1]:
      path.append(start)
   path.reverse()
   return path
#-----#
def bfs(start state, goal state, city graph):
  frontier = collections.deque(city_graph[start_state])
  frontier size = len(frontier)
   explored = \Pi
   explored.append(start state)
  path = ∏
   parent = \{\}
  for city in city graph[start state]:
      parent[city] = start state
  while frontier:
      node = frontier.popleft()
      frontier size = frontier size - 1
      explored.append(node)
      if node == goal state:
         path.append(start state)
         path.append(node)
         return (path, len(explored), frontier_size)
      child list = city_graph[node]
      for child in child list:
         if child not in explored and child not in frontier:
            if child == goal state:
               parent[child] = node
               path = get path(parent, start state, goal state)
              return (path, len(explored), frontier_size)
            parent[child] = node
            frontier.append(child)
            frontier size = frontier size + 1
   return None
#-----#
def dfs(start state, goal state, city graph):
  frontier = \Pi
  for i in range(len(city_graph[start_state])-1,-1,-1):
      frontier.append(city graph[start state][i])
  frontier_size = len(city_graph[start_state])
   explored = \Pi
   explored.append(start_state)
   parent = \{\}
  for city in city_graph[start_state]:
      parent[city] = start_state
   path = \Pi
  while frontier:
      node = frontier.pop()
      frontier size = frontier size - 1
```

```
explored.append(node)
      if node == goal state:
         path = get path(parent, start state, goal state)
         print 'dfs explored:', explored
         return (path,len(explored), frontier size)
      child list = city graph[node] #the neighbors of the current city
      for child in child list:
         if child not in explored and child not in frontier:
            parent[child] = node
      frontier.extend(child for child in child list if child not in explored and child not in frontier)
      frontier size = frontier size + 1
   return None
#-----#
def depth limited search(start state, goal state, city graph, limit):
   parent = {}
  for city in city_graph[start_state]:
      parent[city] = start state
   explored = \Pi
   def recursive dls(node, goal state, city graph, limit, parent, explored):
      explored.append(node)
      if node == goal state:
      # print 'parent1:', parent
         result = get path(parent, start state, goal state)
         return (result, len(explored), len(parent)*limit)
      elif \lim_{t\to 0}:
         return 'cutoff'
      else:
         cutoff occurred = False
         child list = city graph[node]
         for child in child list:
            parent[child] = node
            result = recursive_dls(child, goal_state,city_graph, limit - 1, parent, explored)
            if result == 'cutoff':
               cutoff occurred = True
            elif result is not None:
            # print 'paren2:', parent
               result = get_path(parent, start_state, goal_state)
               return result
         return 'cutoff' if cutoff occurred else None
   return recursive dls(start state, goal state, city graph, limit, parent, explored)
def ids(start state, goal state, city graph):
  for depth in xrange(10):
      result = depth limited search(start state, goal state, city graph, depth)
      if result != 'cutoff':
         return result
  return None
#-----#
def cost(goal state, city location):
   staright_line_distance = {}
  for i in city location:
```

```
dist = dist_cost(city_location[i], city_location[goal_state])
      staright line distance[i] = dist
   distance = sorted(staright line distance.items(), key = lambda x:x[1])
   dict distance = collections.OrderedDict()
   for i in range(len(distance)):
      dict distance[distance[i][0]] = distance[i][1]
  print "staright line distance:", dict distance
   return dict distance
def best_first_search(start_state, goal_state, city_graph, f): #have a list with all the distance of
neighbor to the goal state
   frontier = Queue.PriorityQueue()
   for city in city graph[start state]:
      frontier.put([f[city], city]) # frontier = [[1, 'A'], [2, 'B'], [3, 'C']]
   frontier size = frontier.qsize()
   parent = {}
   for city in city_graph[start_state]:
      parent[city] = start state
   explored = \Pi
   explored.append(start state)
   while not frontier.empty():
      city = frontier.get()
      frontier_size = frontier_size - 1
      node = citv[1]
      explored.append(node)
      if node == goal state:
          path = get_path(parent, start_state, goal_state)
          return (path, len(explored), frontier_size)
      child list = city graph[node]
      for child in child list:
         frontier list = frontier.queue
         frontier city = \Pi
         for i in range(len(frontier list)):
             frontier_city.append(frontier_list[i][1])
         if child not in explored and child not in frontier_list:
             parent[child] = node
             frontier.put([f[child], child])
             frontier size = frontier size + 1
   return None
#-----#
def A star search(start state, goal state, city graph, city location, h): ##have a list with all the
distance of neighbor to the goal state
   frontier = Queue.PriorityQueue()
   for city in city_graph[start_state]:
      frontier.put([h[city], city]) # frontier = [[1,'A'],[2, 'B'],[3, 'C']]
   frontier_size = frontier.qsize()
   parent = {}
   for city in city_graph[start_state]:
      parent[city] = start_state
   explored = \Pi
   explored.append(start state)
   # g is real cost from start to the current
   g = \{\}
```

```
for city in city_graph[start_state]:
      dist = dist cost(city location[city], city location[start state])
      g[city] = dist
   while not frontier.empty():
      city = frontier.get()
      frontier size = frontier size - 1
      node = city[1]
      explored.append(node)
      if node == goal state:
         path = get path(parent, start state, goal state)
         return (path, len(explored), frontier_size)
      child list = city_graph[node]
      for child in child list:
         dist = dist cost(city location[child], city location[node])
         ## get a city list
         frontier list = frontier.queue
         frontier city = \Pi
         for i in range(len(frontier list)):
            frontier city.append(frontier list[i][1])
         if child not in explored and child not in frontier list:
            parent[child] = node
            g[child] = g[node]+ dist
            frontier.put([h[child], child])
            frontier size = frontier size + 1
         elif child in frontier list:
            if g[child] < g[node]+dist:
                parent[child] = node
               frontier.put([h[child], child])
               frontier size = frontier size + 1
   return None
#-----#
def draw_graph(city_graph, city_location, path):
   g = nx.Graph() #empty graph
   for node in city graph:
      g.add node(node)
   count = 0
   edge list = ∏
   for node in city graph:
      for neighbor in city_graph[node]:
         if node in path and neighbor in path:
            edge_list.append((node,neighbor))
         if (node.neighbor) not in a.edges():
            g.add edge(node, neighbor, weight = dist cost(city location[node],
city location[neighbor]))
            count = count + 1
   pos = nx.spring layout(g)
   arc weight = nx.get edge attributes(g, 'weight')
   nx.draw networkx(g, pos, node color = ['r' if not node in path else 'b' for node in g.nodes()],
edge_color = ['black' if not edge in edge_list else 'b' for edge in g.edges()])
```

```
nx.draw_networkx_edge_labels(g, pos, edge_labels=arc_weight)
   plt.axis('off')
   plt.show()
   return count
count branches = 0
bfs time complexity = 0
bfs space complexity = 0
bfs_running_time = 0
bfs path len = 0
bfs\_solved = 0
dfs time complexity = 0
dfs space complexity = 0
dfs_running_time = 0
dfs path len = 0
dfs solved = 0
ids time complexity = 0
ids space complexity = 0
ids running time = 0
ids_path_len = 0
ids solved = 0
bestfs time complexity = 0
bestfs_space_complexity = 0
bestfs running time = 0
bestfs path len = 0
bestfs solved = 0
Astar_time_complexity = 0
Astar space complexity = 0
Astar_running_time = 0
Astar path len = 0
Astar solved = 0
for i in range(1):
   city location = create map() #create the map
   start state = chr(ord('A') + random.randint(0,25))
   #need to test if goal state == start state
   goal state = chr(ord('A') + random.randint(0,25))
   while goal_state == start_state:
      goal_state = chr(ord('A') + random.randint(0,25))
   print 'start_state:', start_state
   print'goal_state:', goal_state
   #run bfs
   city_graph = create_graph(city_location)
   bfs start time = time.time()
   bfs_result = bfs(start_state, goal_state, city_graph) #bfs_result = [[path], # of node
explored]
   bfs_end_time = time.time()
```

```
bfs_running_time = bfs_running_time + (bfs_end_time - bfs_start_time)
   bfs path = None
   if bfs result is not None:
      bfs solved = bfs solved + 1
      bfs path = bfs result[0]
      bfs path len = bfs path len + len(bfs path)
      bfs time complexity = bfs time complexity + int(bfs result[1])
      bfs space complexity = bfs space complexity + int(bfs result[2])
   print 'bfs path:', bfs path
   #run dfs
   city graph = create graph(city location)
   dfs start time = time.time()
   dfs result = dfs(start state, goal state, city graph)
   dfs end time = time.time()
   dfs_running_time = dfs_running_time + (dfs_end_time - dfs_start_time)
   dfs path = None
   if dfs result is not None:
      dfs solved = dfs solved + 1
      dfs path = dfs result[0]
      dfs path len = dfs path len + len(dfs path)
      dfs time complexity = dfs time complexity + dfs result[1]
      dfs_space_complexity = dfs_space_complexity + dfs_result[2]
   print 'dfs path:', dfs path
   #run ids
   city_graph = create_graph(city_location)
   ids start time = time.time()
  ids result = ids(start state, goal state, city graph)
   ids end time = time.time()
  ids running time = ids running time + (ids end time - ids start time)
   ids path = None
  if ids result is not None:
      ids solved = ids solved + 1
      ids path = ids result[0]
      ids path len = ids path len + len(ids path)
      ids_time_complexity = ids_time_complexity + ids_result[1]
      ids_space_complexity = ids_space_complexity + ids_result[1]
   print 'ids_path:', ids_path
   #run best first search
   city graph = create graph(city location)
   bestfs_start_time = time.time()
   staright distance togoal = cost(goal state, city location)
   bestfs_result = best_first_search(start_state, goal_state, city_graph,
staright distance togoal)
   bestfs end time = time.time()
   bestfs running time = bestfs running time + (bestfs end time - bestfs start time)
   bestfs path = None
   if bestfs result is not None:
      bestfs solved = bestfs solved + 1
      bestfs path = bestfs result[0]
      bestfs path len = bestfs path len + len(bestfs path)
      bestfs_time_complexity = bestfs_time_complexity + bestfs_result[1]
```

```
bestfs_space_complexity = bestfs_space_complexity + bestfs_result[2]
   print 'bestfs path', bestfs path
   #run A*
  city graph = create graph(city location)
   Astar start time = time.time()
   estimate staright distance togoal = cost(goal state, city location)
   Astar result = A star search(start state, goal state, city graph, city location,
estimate staright distance togoal)
  Astar end time = time.time()
  Astar running time = Astar running time + (Astar end time - Astar start time)
  Astar path = None
  if Astar result is not None:
     Astar_solved = Astar_solved + 1
     Astar path = Astar result[0]
     Astar path len = Astar path len + len(Astar path)
     Astar time complexity = Astar time complexity + Astar result[1]
     Astar space complexity = Astar space complexity + Astar result[2]
   print 'Astar path:', Astar path
   city_graph = create_graph(city_location)
   print city graph
  count branches = count branches + draw graph(city graph, city location, bfs path)
#-----#
average branches = count branches/100
print average branches
average bfs time complexity = bfs time complexity/100
average bfs space complexity = bfs space complexity/100
average_bfs_running_time = bfs_running_time/100
average bfs path len = bfs path len/100
print 'average_bfs_time_complexity:', average_bfs_time_complexity
print 'average bfs space complexity:', average bfs space complexity
print 'average_bfs_running_time:', average_bfs_running_time
print 'average bfs path len:', average bfs path len
print 'bfs_solved:', bfs_solved
average_dfs_time_complexity = dfs_time_complexity/100
average dfs space complexity = dfs space complexity/100
average dfs running time = dfs running time/100
average_dfs_path_len = dfs_path_len/100
print 'average dfs time complexity:', average dfs time complexity
print 'average_dfs_space_complexity:', average_dfs_space_complexity
print 'average dfs running time:', average dfs running time
print 'average_dfs_path_len:', average_dfs_path_len
print 'dfs solved:', dfs solved
average ids time complexity = ids time complexity/100
average ids space complexity = ids space complexity/100
average ids running time = ids running time/100
average ids path len = ids path len/100
print 'average_ids_time_complexity:', average_ids_time_complexity
```

```
print 'average_ids_space_complexity:', average_ids_space_complexity print 'average_ids_running_time:', average_ids_running_time print 'average_ids_path_len:', average_ids_path_len print 'ids_solved:', ids_solved
```

```
average_bestfs_time_complexity = bestfs_time_complexity/100 average_bestfs_space_complexity = bestfs_space_complexity/100 average_bestfs_running_time = bestfs_running_time/100 average_bestfs_path_len = bestfs_path_len/100 print 'average_bestfs_time_complexity:', average_bestfs_time_complexity print 'average_bestfs_space_complexity:', average_bestfs_space_complexity print 'average_bestfs_running_time:', average_bestfs_running_time print 'average_bestfs_path_len:', average_bestfs_path_len print 'bestfs_solved:', bestfs_solved
```

```
average_Astar_time_complexity = Astar_time_complexity/100 average_Astar_space_complexity = Astar_space_complexity/100 average_Astar_running_time = Astar_running_time/100 average_Astar_path_len = Astar_path_len/100 print 'average_Astar_time_complexity:', average_Astar_time_complexity print 'average_Astar_space_complexity:', average_Astar_space_complexity print 'average_Astar_running_time:', average_Astar_running_time print 'average_Astar_path_len:', average_Astar_path_len print 'Astar_solved:', Astar_solved
```