CS182 Artificial Intelligence Project
Safe Cycling Route Planning

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1 Introduction

The goal of our project is to create a routing system for bicycle trips that takes into account more than just distance. Current map applications like Google often route cyclists through busy streets and intersections, resulting in unnecessarily dangerous trips and sometimes accidents. The algorithm we chose to use for this problem is A* search with a variety of cost functions and heuristics incorporating distance, safety of a given route, and changes in elevation (also important for biking but not information Google maps currently considers).

Additionally, we considered the problem of finding a central meeting place for two or more cyclists starting from different positions. To solve this optimization problem, we used k-beam search and simulated annealing.

The graph search problem is directly analogous to techniques and ideas from the class: using intersections as nodes in the graph and road segments connecting intersections as paths, we are able to construct the city maps as directed graphs. From there, we can use data generated from a variety of sources to come up with approximate costs associated with paths and related heuristics at nodes.

The optimization techniques we use are also direct applications of algorithms from the optimization portion of the course.

Problem-specific adaptations were largely limited to the collection and interpretation of relevant data and the development of a cost function and relevant heuristics.

2 Background and Related Work

While our problem was fairly straightforward, we did do some research to get ideas for potential cost attributes and data sources. Our initial formulation of the problem, for example, did not include elevation differencing, but reading previous studies led us to believe that this was an important criterion [1].

3 Problem Specification

3.1 Cost Functions

The problem that we are solving is of the general class of graph search problems. Given a strongly connected graph, we seek to minimize some cost function:

$$cost = \sum_{i=0}^{n} cost(path_i) \tag{1}$$

given that:

- $path_0 \in Connections_{\text{(starting node)}}$
- $path_i, path_{i+1} \in Connections_{node_j}$
- $path_n \in Connections_{\text{(target node - 1)}}$

Specifically for our problem, we created three different cost functions:

$$cost_{distance\_only}(path_i) = length_i \tag{2}$$

$$cost_{distance\_safety}(path_i) = (\alpha \times length_i) \times (\beta \times accidents_i) \tag{3}$$

$$cost_{distance\_safety\_elevation}(path_i) = (\alpha \times length_i) \times (\beta \times accidents_i) + abs(\Delta elevation_i) \tag{4}$$

Where α and β are scaling multipliers to weight the relavitve magnitudes of the different cost measurements (e.g. if length should be scaled to 500m and $\delta elevation$ in meters). In the optimization portion of our project, we seek to minimize the total cost to all parties:

$$min(\sum_{j}^{n} cost_j) \tag{5}$$

where $cost_j$ is the cost to participant j.

3.2 Heuristic Functions

We used three main heuristic functions for testing the A* algorithm. We firstly used a null heuristic that we use as a baseline to compare the other heuristics against. We used a simple euclidean distance heuristic that measures the distance from the current node i to the goal node as an admissible and consistent heuristic. Finally we used a heuristic that makes a simple delta elevation estimate from the current goal to the end goal and a minimum of the number of accidents on the connections from the current goal. This 'combined heuristic' also included the euclidean distance element and a linear combination of these values was used.

$$heuristic_{null}(node_i) = 0 \tag{6}$$

$$heuristic_{euclidean\_distance}(node_i) = euclidean\_distance(node_i, goal) \tag{7}$$

$$\begin{aligned} heuristic_{combined}(node_i) = {} & (\alpha \times euclidean\_distance(node_i, goal) \\ & \times (\beta \times min(accidents\_node_i)) \\ & + abs(elevation\_difference(node_i, goal)) \end{aligned} \tag{8}$$

4 Approach

Data Structures: Our primary data structures are an intersection graph, which is stored as a Python dictionary, and a connection dictionary, which is also stored as a Python dictionary. The intersection graph maps nodes (intersections) by id to a list of paths (road segments) from that node. The connection dictionary maps a connection (road segment) to its source node, sink node, and various cost parameters (in our case distance, number of bicycle crashes on that road segment, and change in elevation over that road segment).

Algorithm 1 A-Star Search

```
function A-STAR-SEARCH(graph, startnode, targetnode)
    node ←a node with STATE = startnode
    PATH-COST ← heuristic(startnode, targetnode)
    frontier ← a priority queue ordered by PATH-COST + heuristic(node, targetnode) with node
as the only element
    explored ← an empty set
    loop
        if EMPTY?(frontier) then
            return failure
        end if
        node ← POP(frontier) /*chooses the lowest cost+heuristic node in frontier */
        if node == targetnode then
            return SOLUTION(node)
        end if
        add node.STATE to explored
        for each path in PATHS(node) do
            child ← child-node(node, path)
            if child.STATE is not in explored or frontier then
                frontier ← insert(child, frontier)
            else if child.STATE is in frontier with higher PATH-COST + heuristic then
                replace that frontier node with child
            end if
        end for
    end loop
end function
```

Algorithm 2 Simulated Annealing Meeting Spot

function SIMULATED ANNEALING MEETING SPOT($graph, startingpts, cost, heuristic$)
  if length$(startingpts) < 2$ **then**
    return error
  end if
  $current \leftarrow$ **mean**$(startingpts)$.CLOSEST-NODE
  $temperature \leftarrow e^{10}$
  $\gamma \leftarrow .5$ /*schedule to manage $temperature$ */
  while $temperature > e^{-2}$ **do**
    $temperature \leftarrow temperature * \gamma$
    $next \leftarrow$ a randomly selected *child* of *current*
    $current$.VALUE $\leftarrow \sum_{pt \in startingpts}$ **cost**$(pt, centroid)$
    $next$.VALUE $\leftarrow \sum_{pt \in startingpts}$ **cost**$(pt, next)$
    $\Delta E \leftarrow next$.VALUE $-$ $current$.VALUE
    if $\Delta E > 0$ **then**
      $current \leftarrow next$
    else
      $current \leftarrow next$ with probability $e^{\Delta E / temperature}$
    end if
  end while
end function

Algorithm 3 K-Beam Search Meeting Spot

function K-BEAM SEARCH MEETING SPOT($k, graph, startingpts, cost, heuristic$)
  if length$(startingpts) < 2$ **then**
    return error
  end if

  $\{candidatenodes\} \leftarrow node \,\forall\, node \in graph$ s.t.
$node.x \geq min(startingpts.x)$& $node.x \leq max(startingpts.x)$&
$node.y \geq min(startingpts.y)$& $node.y \leq max(startingpts.y)$

  $point_i \leftarrow$ a randomly selected $node \in \{candidatenodes\} \forall i \leq k$
  $best$.VALUE $\leftarrow min_{i \leq k}(\sum_{pt \in startingpts}$ **cost**$(pt, point_i))$
  while True do
    $\{nextcosts\} \leftarrow \sum_{pt \in startingpts}$ **cost**$(pt, child_i) \forall i \leq k, child_i \in$ PATHS$(point_i).endnode$
    $point_i \leftarrow$ i-th least $node \in \{nextcosts\} \forall i \leq k$
    $next$.VALUE $\leftarrow \sum_{pt \in startingpts}$ **cost**$(pt, point_1)$
    if $next$.VALUE $<$ $best$.VALUE **then**
      $best \leftarrow next$
    else
      break
    end if
    return *best*
  end while
end function

5 Experiments

We aimed to test:

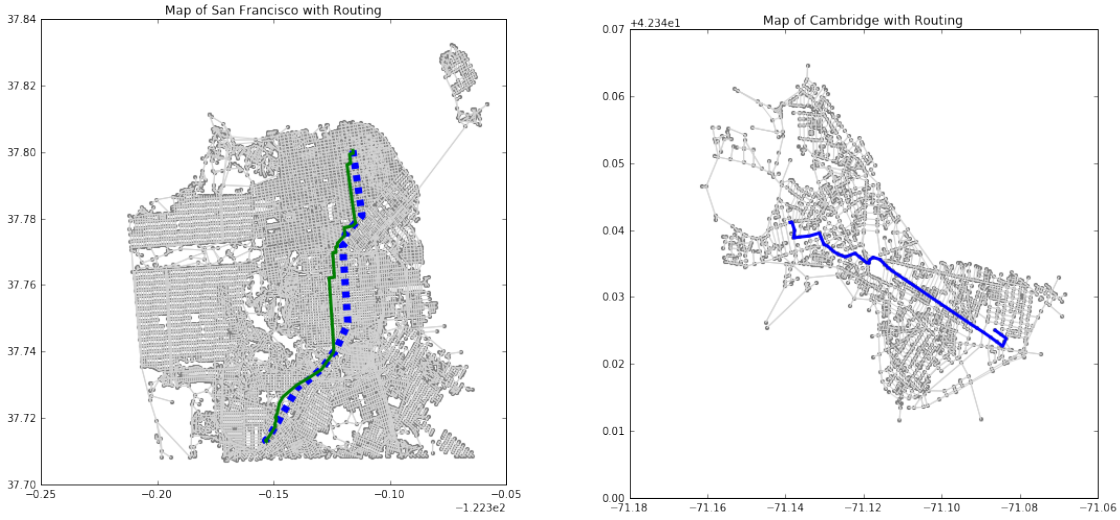
- The effect of the varying cost functions on the routes that were found.
- The effect of the A^* heuristic on the speed of search (and consistency of the route)
- The efficiency and effectiveness of the resulting search

5.1 Data Collection, Extraction and Preprocessing

We tested our implementation on data from the cities of Cambridge, MA and San Francisco, CA. GIS location data is available on the local government websites in the form of a pandas geojson dataframe and was easily read into a pandas dataframe object using the geopandas library [1].

As discussed above, these geolocation data are used to create a set of nodes with coordinate positions and a number of connections which define the roads and the intersections that those roads are connected to. The data from Cambridge contained routing errors were some intersections were connected to other incorrect intersections resulting in roads that spanned the entire graph rather

[1] `http://geopandas.org/`



(a) San Francisco

(b) Cambridge

Figure 1: Connected graphs of the San Francisco and Cambridge maps with a route shown on the map (using only distance as the cost metric on the Cambridge but distance and safety on the San Francisco map).

than simply connecting the two nearest neighboring intersections. The solution to this was to use the *geometry* data within the Pandas geolocation dataframe and the *shapely* [2] graphing library to compare the actual road length to our interpolated distance for the road. If the interpolated distance was incorrect by more than a factor of 10, we made the assumption that the nodes were incorrectly tagged in the data and we dropped the connection attribute. The elevation and crash data was independently collected from the different government websites and the intersection id's were used to map this data into the 'intersection' and 'connection' graphs and dictionaries.

The resulting connected graphs for 'Cambridge' and 'San Francisco' are shown in figure 1

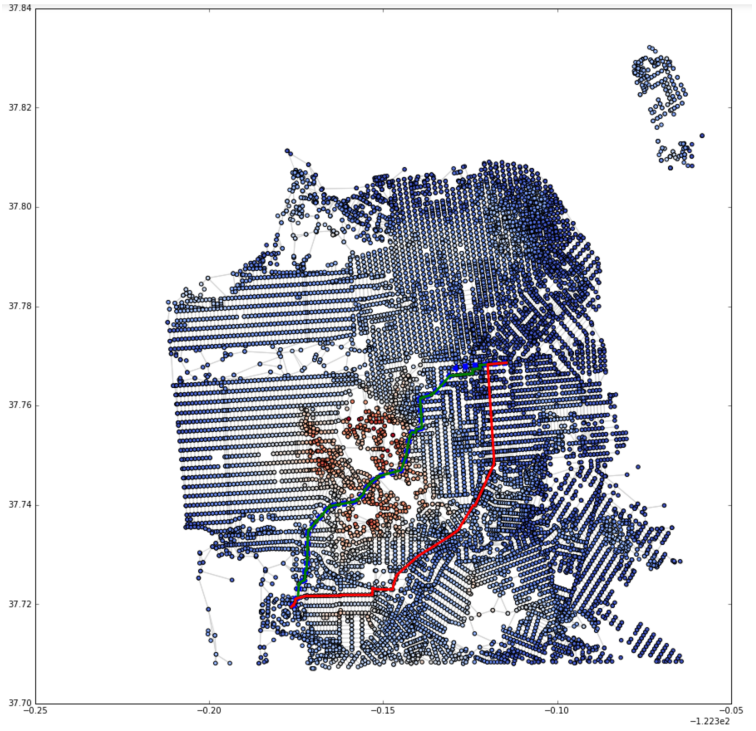
5.2 Testing A^* Search

We randomly selected nodes within the two graphs and ran A* search to find the optimal route through the map. The figure **??** shows an example of A* finding an optimal route under two different costs.

We then ran an iteration of 100 simulations for each cost function (2) and each heuristic function (6). Specifically the null and euclidean heuristics are both expected to find the optimal route. The euclidean heuristic should explore fewer nodes than the null heuristic. When the cost function is simple distance or simple distance and safety, the combined heuristic is neither admissible nor is it consistent as it is penalizing nodes for a cost that is not encoded in the algorithm. We expect to see this algorithm find a 'longer than necessary optimal path'. However, when the cost function also encodes all of these costs, we now expect the combined heuristic to out perform the other heuristics on all accounts. Please refer to Results for a further discussion on the above.

[2] https://pypi.python.org/pypi/Shapely

Figure 2: Paths between nodes in San Francisco. Blue path optimizes for distance only, green path avoids previous bicycle accidents, and red path minimizes altitude changes. Overlaid with an altitude plot of San Francisco, we can clearly see the red path avoiding a hill.



- Analysis: To test our algorithms, we built graphs on GIS data from both Cambridge, MA and San Francisco, CA (supplemented with elevation and crash data collected from other sources as necessary). We ran both the single-path and meeting point algorithms for a variety of cost functions and start and end points and were pleased to see that the paths generated by our algorithms when taking into account safety and elevation factors do indeed seem to avoid busy intersections and steep hills in a reasonable way.
- Evaluation: We went through a few iterations of tuning the parameters in our cost function to get the appearance of the graphs to mimic what we think we'd want as cyclists. Because the cost in our problem is qualitative rather than explicitly quantitative, we were largely forced to estimate parameters based on what we thought would be reasonable rather than deriving them from empirical data of some sort. That said, we all felt that with our final parameters the algorithm was doing a reasonable job at generating routes we would want.
- Critique: Our algorithms could have been made to run somewhat faster by incorporating pruning strategies but we were generally satisfied with run times. Additionally, it was difficult to generate a very useful admissible heuristic for bike crashes because one could almost always find an extremely convoluted path to avoid almost all of them, and so to have a heuristic which is always *le* the actual cost to the goal is often not that informative.

	Time	Total Cost
Simulated Annealing		
K-Beam Search		

Table 1: Description of the results.

5.3 Results

Comparison of routes found by three different cost functions to A* with three different heuristics:

Figure 3: Basic road cost under three different heuristics. Here we would expect the combined heuristic to significantly underperform the null heuristic and euclidean heuristic in terms of distance as the heuristic does not properly model the cost function. Therefore the heuristic is both inadmissible and inconsistent for this problem.

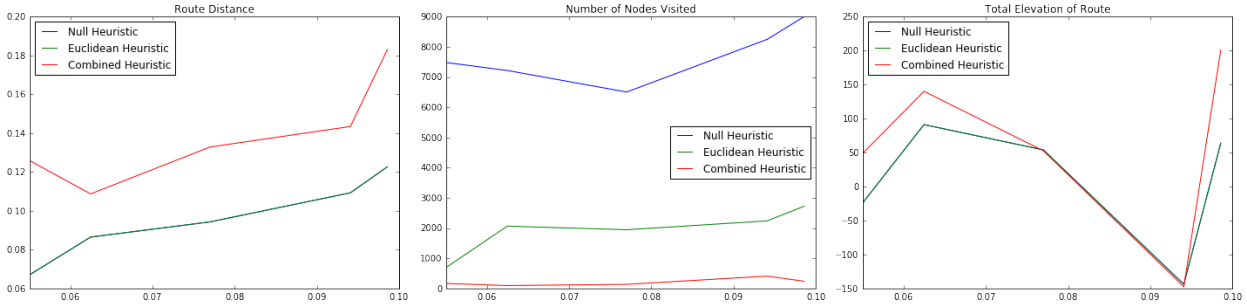


Figure 4: Safety road cost under three different heuristics. Again, we expect to see the combined heuristic underperform the null heuristic and euclidean heuristic as the heuristic does not properly model the cost function and is neither admissible nor consistent

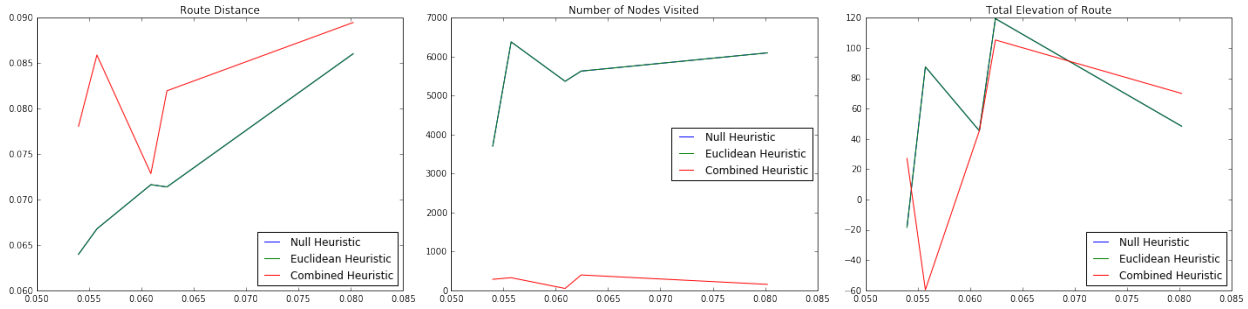


Figure 5: Safety, distance, and elevation cost under three different heuristics. Here we still do not expect the combined heuristic to find the ideal solution, as the heuristic is not consistent, but it should do a reasonable job and significantly decrease the nodes expanded.

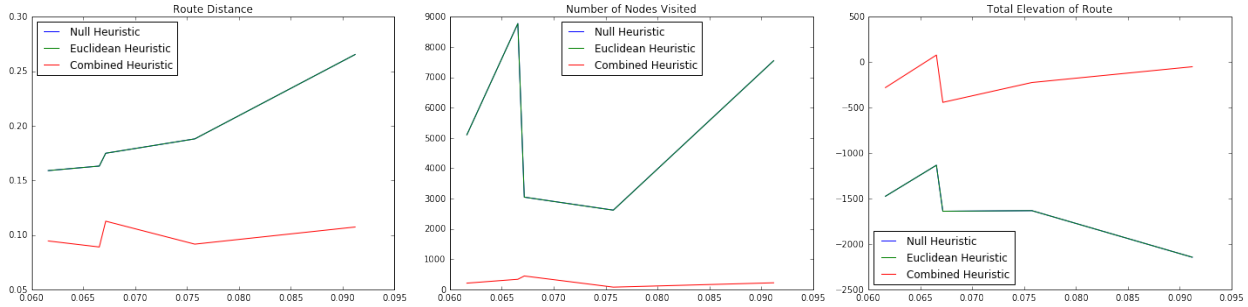
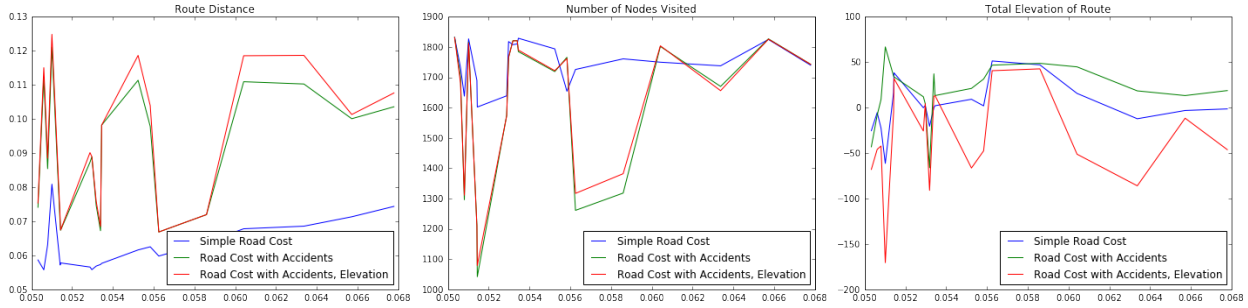


Figure 6: Total distance, total nodes expanded, and total elevation change for the three cost functions under uniform cost search.



TODO: Comparison of K-beam search and Simulated annealing: time to find solution vs total cost of solution found for a number of trials

6 Discussion

The graph search approach is a very straightforward and satisfactory solution to this problem. We felt that our results were very reasonable given our preexisting knowledge of Cambridge and San Francisco streets.
A couple takeaways from this project:

- As always, you're only as good as your data. We had some lofty goals for the data that we'd be able to collect and use for this project, but even the data we ended up using was harder to collect and map that we anticipated, and much of the crash data was a few years old. Cambridge and San Francisco are relatively tech-forward cities, so I can imagine this would be even more difficult in most other environments
- It was interesting to see how our algorithm scaled to the larger map of San Francisco. To plan routes through a larger area, it's clear that we would have to adapt the algorithm to get the runtime within a reasonable range. In particular, we found in our reading that many routing engines actually use inadmissible heuristics for these tasks and still find reasonable results but in a much quicker time.

In future work, we could develop faster algorithms by using pruning procedures or finding ways to run expensive operations in parallel or vectorized forms. We could develop more sophisticated models of biking comfort by also including road construction data and pothole reports.

A System Description

The easiest way to use our system is to open the provided iPython notebook and run each of the cells. All of the supporting functions can be found in *final_project.py*.[3][4]

B Group Makeup

1. Nick Hoernle
   (a) Creation of graph dictionary structure and A*search algorithm
   (b) Simulated annealing
2. Nikhila Ravi
   (a) K-Beam Search
   (b) Visualization and analysis of results of graph search algorithms
3. Anna Sophie Hilgard
   (a) Construction of Datasets
   (b) Research and Implementation of more complicated cost functions and heuristics

[3] *final_project.py*: `https://github.com/NickHoernle/Artificial-Intelligence-CS182-Project/blob/master/final_project.py`
[4] *final_project.ipynb*: `https://github.com/NickHoernle/Artificial-Intelligence-CS182-Project/blob/master/final_project.ipynb`

References

[1] Jan Hrncir, Palov Zilecky, Qing Song, and Michal Jakob. Practical multicriteria urban bicycle routing. *IEEE Transactions on Intelligent Transportation Systems*, PP(99):1–12, 2016.