# CS182 Artificial Intelligence Project
## Safe Cycling Route Planning

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## 1 Introduction

Biker safety and biker safety awareness has been a topical issue for a number of years with the biker death toll at an unacceptably high rate (13 deaths in the past 5 years in Boston alone (**count of accidents in Cambridge - do we have a date attached here??**)). Current map applications like Google often route cyclists through busy streets and intersections, resulting in unnecessarily dangerous trips. The purpose of this project has been to explore AI graph search and local search algorithms to optimize a bike routing algorithm not only for 'distance minimization', but also for 'path safety' and 'elevation comfort'. We explore the use of A* graph search under different cost and heuristic metrics to obtain a fast, yet reliable graph search between any two nodes on the intersection graph. Furthermore, we explore the use of local search to optimize for the ideal meeting point between two or more cyclists.

## 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

The graph of intersections and nodes forms a highly connected state space (Cambridge has 1831 nodes, San Francisco has 18410 nodes, and each node typically has a branching factor of 4). While it is possible, searching the entire state space for San Francisco would involve considerable computation, on the order of $4^{18410}$ possible routes to explore, and this search space grows exponentially with additional nodes. Since our aim is to design a scalable algorithm, this was simply not feasible.

To compound this search space problem, we aimed to determine central meeting areas for a number of cyclists to use as a fair and safe meeting place. The search problem here is therefore not only to determine the best route from a start node to a goal but also to determine the best goal node, optimizing for minimal cost for all cyclists.

Initially, we implement an A* search algorithm. We then used that A* search as a baseline for determining the route from any starting point to some goal node and we run a local search layer on top of this to find the best meeting intersection between a number of cyclists. We tailored three cost functions and three heuristics for comparing the performance of the A* and Local Search (which depend on the A* algorithm).

### 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 $\alpha$ and $\beta$ 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

### 4.1 Data Structures

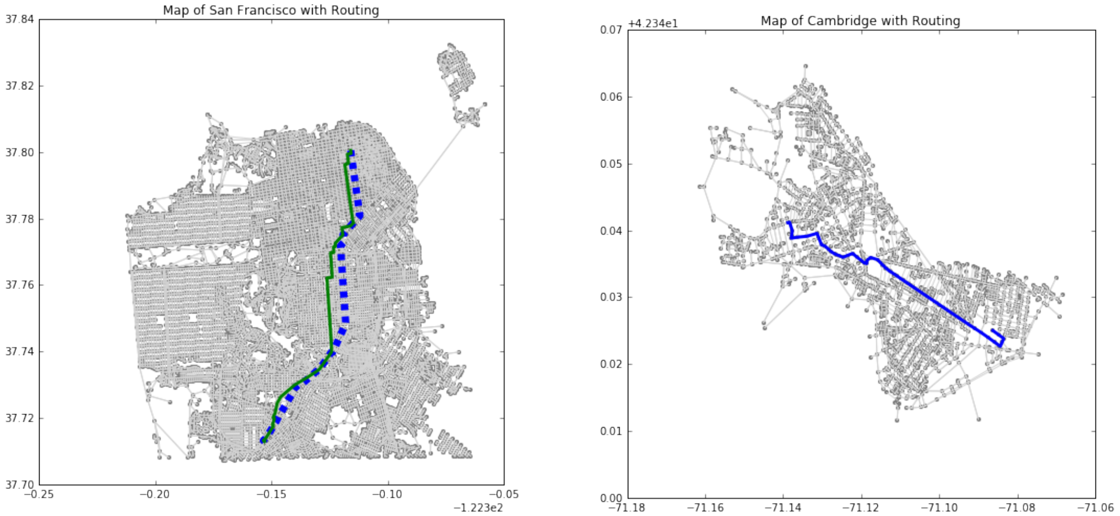
Our primary data structures are an intersection graph, which is stored as a Python dictionary, and a connection dictionary, which is also stored as a Python dictionary. The intersection graph maps nodes (intersections) by id to a list of paths (road segments) from that node. The connection dictionary 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).

### 4.2 Data Collection, Extraction and Preprocessing

In this case study, we were able to use open source geolocation data from Cambridge and San Francisco city councils. These departments further supplied data on the number of bike related accidents for various road segments. Lastly an elevation layer from the open GIS websites was used to infer the elevation of certain roads and intersections.

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].

[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).*

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 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

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

### 4.3 A$^*$*Search*

### 4.4 Local Search: Simulated Annealing

### 4.5 Local Search: K-Beam Search

## 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 Testing $A^*$ Search

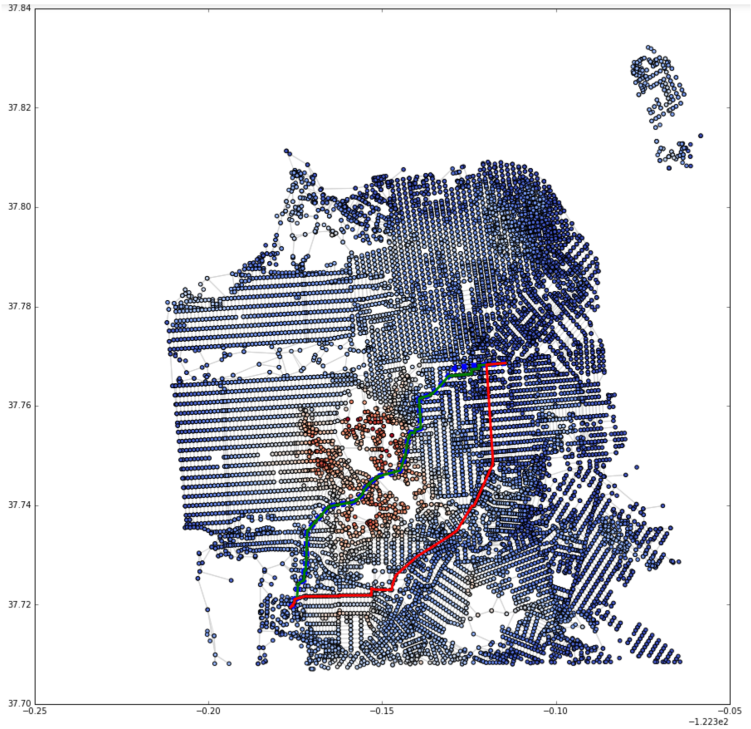
We randomly selected nodes within the two graphs and ran A* search to find the optimal route through the map. The figure **??** shows an example of A* finding an optimal route under two different costs.

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.

### 5.2 Testing Local Search

The Simulated Annealing Search involved initializing a centroid and iteratively hill climbing the space around that centroid to find a local optimum point. Initially, a temperature attribute is set high, such that the hill climbing algorithm accepts non-optimal nodes with a high probability. As the algorithm proceeds, and converges on a local optimum, the temperature is decreased such that the hill climbing becomes more deterministic.

*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.*



As the state space of the search graph is large, and the distance metric is highly interpretable, we opted to initialize the first centroid at the intersection that represents the Euclidean mean between all cyclists. Our aim was to initialize the centroid within the vicinity of an optimal meeting point and allow the high initial temperature to counteract any potential local optimum intersections that may have been encountered.

K Beam search involved initializing a number of centroids within the state space of the graph and iteratively hill climbing from the K best centroids to find a local optimum.

We ran Simulated Annealing and K-Beam Search on a number of different iterations of randomly selected nodes. While both algorithms can be tuned to run faster (by reducing the temperature faster for simulated annealing and reducing 'k' for k-beam search at the cost of being more susceptible to local minima) we can make a reasonable comparison of the two algorithms in terms of their total runtime resulting cost of the returned node.

## 6 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.*

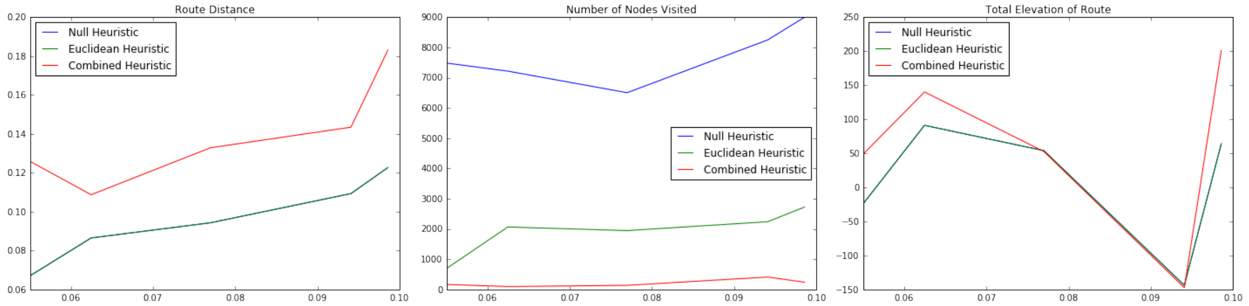


*Figure 4: Safety road cost under three different heuristics. Again, we expect to see the combined heuristic underperform the null heuristic and euclidean heuristic as the heuristic does not properly model the cost function and is neither admissible nor consistent*

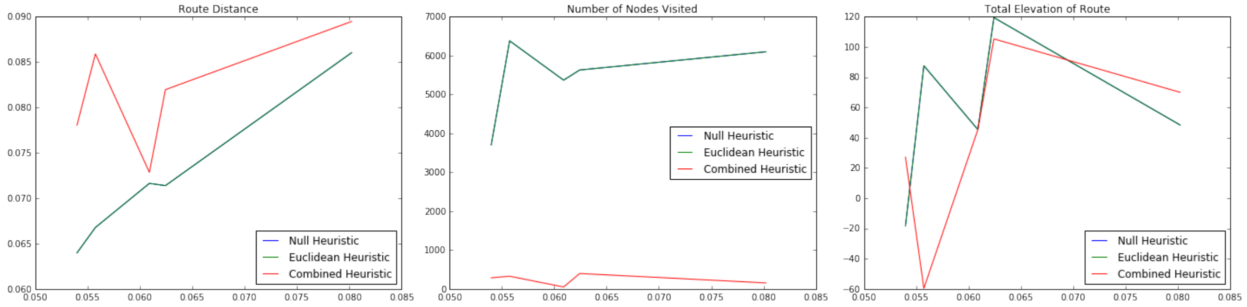


*Figure 5: Safety, distance, and elevation cost under three different heuristics. Here we still do not expect the combined heuristic to find the ideal solution, as the heuristic is not consistent, but it should do a reasonable job and significantly decrease the nodes expanded.*

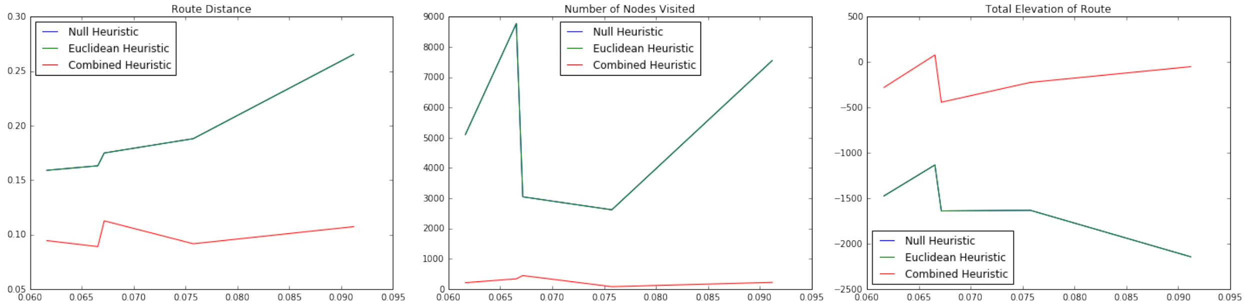
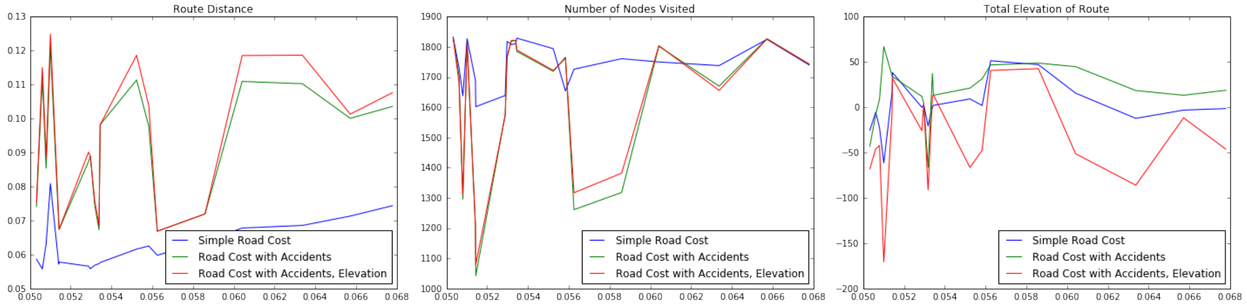


*Figure 6: Total distance, total nodes expanded, and total elevation change for the three cost functions under uniform cost search.*



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

## 7 Discussion

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.

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.

Bayesian Inference: Calculating the number of accidents per road segment is a good estimate of how dangerous a given road segment is, but probably a better indicator would be accidents per units of bicycle traffic. If we were able to collect bicycle traffic data for each road segment, we could then calculate the Bayesian probability of P(road segment — accident) as proportional to P(accident — road segment) * P(road segment). In particular, we may be over-penalizing roads with a large amount of cycling traffic.

Pruning techniques: To make the search algorithms run faster, we could consider a number of pruning techniques to reduce feasible paths at each node.

## 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

# C Algorithms

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

## 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.