

PROJECT REPORT

Minimal Time Paths

*Alex Dunkel, Roy Gullem, Keith Houpy,
Emily Ribando-Gros, and Vincent Rodomista*

CSC 4444

December 8, 2016

Contents

1	Motivation	2
2	Problem	2
2.1	Problem Formulation	2
3	AI Concepts	2
3.1	Search Tree	2
3.1.1	Node	2
3.1.2	Frontier	3
3.2	Constraints	3
3.2.1	Branching Factor	3
3.2.2	Driving Assumptions	3
4	Search Strategies and Experimentation	4
4.1	Uniform Cost Search	4
4.1.1	UCS Experiment : Amite, LA to Stockton, CA and Hayward, CA	4
4.1.2	Minimum time with minimum price flights	4
4.1.3	Minimum time with minimum price flights and limit	5
4.1.4	Minimum time with minimum time flights	5
4.1.5	Minimum price with minimum price flights	5
4.2	A* Search with Straight Line Heuristic	6
4.2.1	A* Experiment : Estimating Time based on Distance	6
4.2.2	Conclusion	6
5	Software System Design and Implementation	7
5.1	Search Classes	7
5.2	Map Utilities	8
5.2.1	Road Distance and Driving Calculator	8
5.3	APIs	9
5.4	Caching	10
6	Future Work	10

1 Motivation

Travel plans can be extremely complicated. As a college student, when planning a trip, you can sift through numerous flights looking for deals and also weigh the cost of driving based on gas prices and car mileage. On the other hand, a business person may do the same sort of sifting to find the fastest, most direct flights and available private transportation in order to get to their destination as fast as possible without considering the price. We are given many options when considering travel plans, and planning could end up in a series of calculations based on time, price of travel, or both.

2 Problem

We want to find the path from one point to another by minimizing time or price by either driving, flying, or a combination of both. To ensure that the price of this path is not too high, we can specify a price limit so that we find the fastest path under that price limit.

2.1 Problem Formulation

1. **Initial State:** The user's starting point
2. **States:** contact points
3. **Actions:** either fly or drive to a destination. For example, *Drive(destination)* or *Fly(destination)*
4. **Transition Model:** given a state and action moves the user to the new contact point
5. **Goal State:** the user's destination
6. **Path:** a sequence of actions from the initial state to the goal state
7. **Path Costs:** the time or price it takes to get from one contact point to another
8. **Solution:** the path from the initial state to the goal state that does not exceed the price limit

3 AI Concepts

3.1 Search Tree

3.1.1 Node

A Node in the search tree represents a contact point along the path. Node attributes include

- **State :** Information about the contact point such as a name and latitude longitude coordinates
- **Parent :** The node in the search tree which generated this node
- **Action :** The action (fly or drive) applied to the parent to generate this node
- **Path costs in time and price :** the time and price needed to travel from the initial node to the current node

3.1.2 Frontier

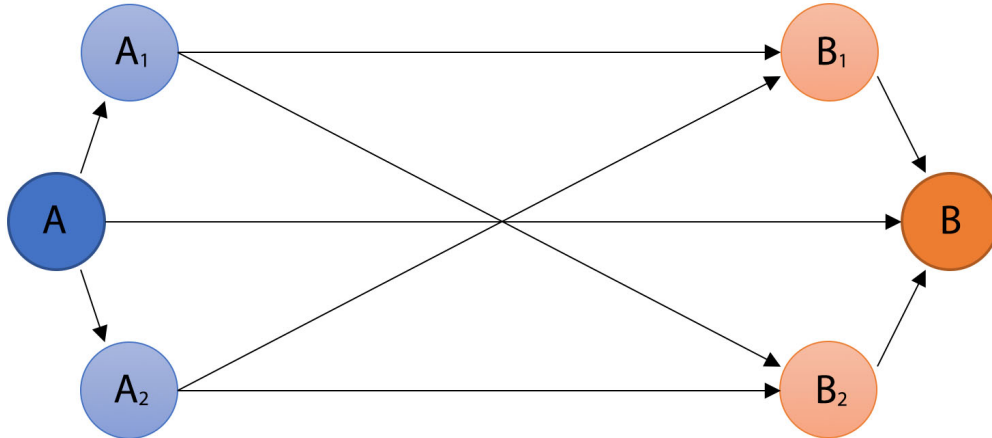
After expanding a leaf node in our search tree, the general search tree algorithm collects the next set of available leaf nodes for expansion in the frontier. But before searching can continue, our algorithm must check whether any of the frontier nodes will result in a path cost price which exceeds the user's price limit. In other words, if the price of a path exceeds the given price limit we do not add the next node to the frontier. This way we can ensure that we never find a path with a price that is above the limit. Nodes are selected for expansion based on the search strategies described in 4.

3.2 Constraints

3.2.1 Branching Factor

When searching for a path, given the number of airports and cities in the US, our branching factor could be very large. Because of this, some constraints must be considered. Let A be the initial starting point and let B be the destination point. We limit the number of airports around A , say $\{A_i\}_{i=1}^n$, and the number of airports around the destination point, say $\{B_j\}_{j=1}^m$. The agent can then drive from A to one of the airports in $\{A_i\}_{i=1}^n$ or drive directly to B . If the agent is at one of the airports in $\{A_i\}_{i=1}^n$, the only option for the agent is to fly to one of the airports in $\{B_j\}_{j=1}^m$. If the agent is at an airport around B , then the only possible action is to drive to the destination B . Figure 1 shows an example with a graph with $n = 2$ and $m = 2$.

Figure 1: Graph example with $n = 2$ and $m = 2$.



3.2.2 Driving Assumptions

In order to calculate driving time and cost, a few assumptions were hard coded into our application. To give a more accurate description of the time it takes to drive across the country, every 12 hours we will assume that our user will spend \$75 on a hotel. We will add this price to our path price when searching for a solution. Similarly, when calculating time we will only assume that the user will drive 12 hours a day. In other words, for every 12 hours of driving, a cost of \$75 is added to the path price and 12 hours are added to the path time. Additionally, we assumed that a car has 35 miles per gallon and a gallon of gas is \$2.15. These assumptions can be seen in 3b.

4 Search Strategies and Experimentation

4.1 Uniform Cost Search

At the base line, our algorithm performs a tree search seeking to minimize the time it takes to travel given a price limit. Since different users may value their time more than their money or may not like driving, we considered the following features.

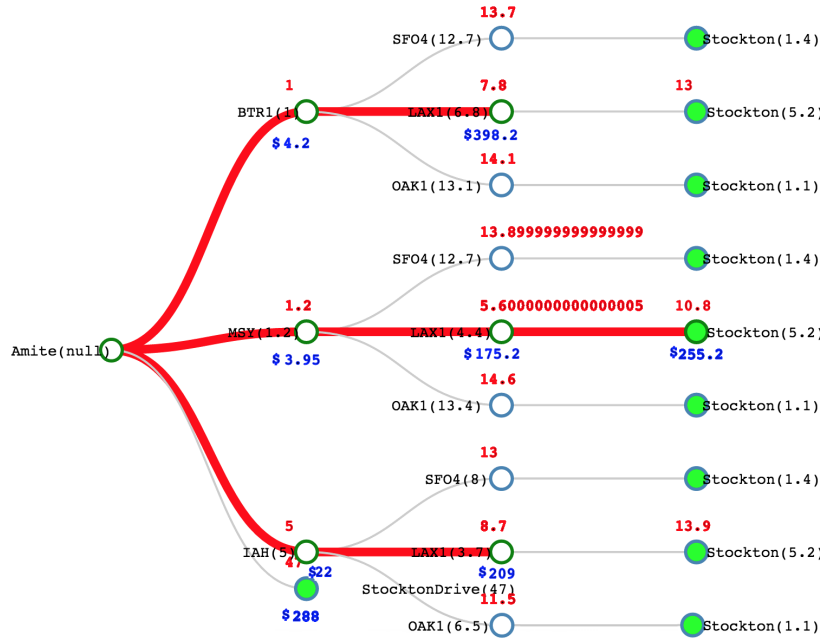
4.1.1 UCS Experiment : Amite, LA to Stockton, CA and Hayward, CA

The following searches were done without a price limit and with a price limit of \$250. At the very bottom of the tree, there is one node to represent the driving distance, which ends up being more expensive than either of the flights we found.

4.1.2 Minimum time with minimum price flights

In the first search, we used UCS minimizing time without a price limit. When choosing flights between two places, we chose the minimum priced flight.

Solution : Amite \rightarrow MSY(1.2 hr) \rightarrow LAX(4.4 hr) \rightarrow Stockton(5.2 hr)
 Total Price: \$255
 Total Time: 10 hrs and 48 min



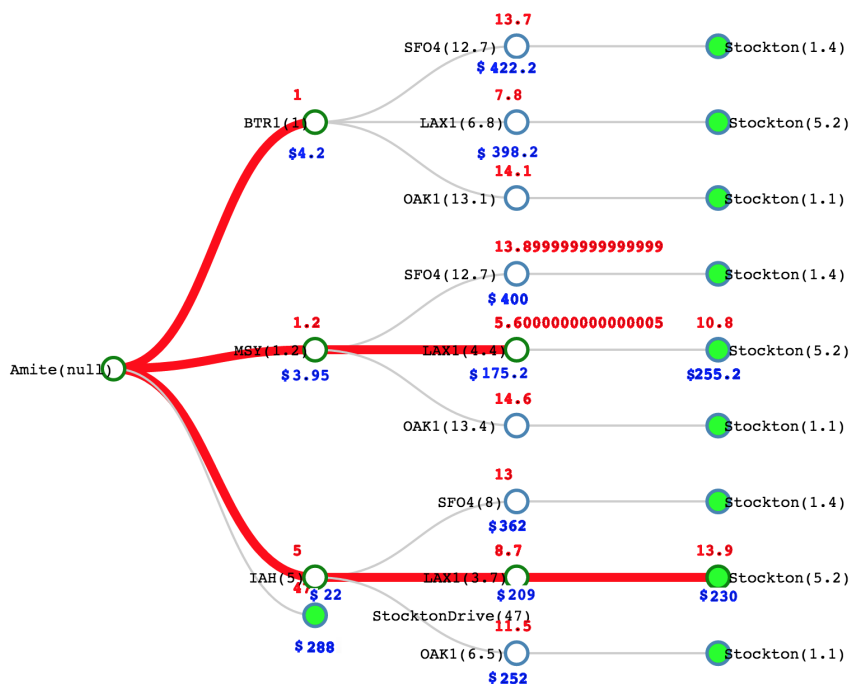
4.1.3 Minimum time with minimum price flights and limit

In the second search, we used UCS minimizing time with a price limit of \$250. When choosing flights between two places, we chose the minimum priced flight.

Solution : Amite \rightarrow IAH(5 hr) \rightarrow LAX1(3.7 hr) \rightarrow Stockton(5.2 hr)

Total Price: \$230

Total Time: 13 hrs and 54 min



In the third search, we used UCS minimizing time. When choosing flights between two places, we chose the minimum priced flight.

Total Price: \$530

In the fourth search, we used UCS minimizing price. When choosing flights between two places, we chose the minimum priced flight.

Total Price: \$287

The Sankey diagram illustrates the flow of data from a source node 'Amite, LA(null)' to various destinations. The flows are color-coded: red for the main path, green for secondary paths, and blue for tertiary paths. The diagram shows a hierarchical structure where the main path splits into three branches, each of which further splits into multiple sub-branches. The destinations are labeled with city names and counts in parentheses.

Source	Intermediate Node	Intermediate Value	Destination	Destination Value
Amite, LA(null)	BTR1(2.91)	\$673.51	SFO4(670.6)	Hayward, CA(5)
		\$410.51000000000005	SJC(407.6)	Hayward, CA(21)
		\$472.51000000000005	OAK1(469.6)	Hayward, CA(4)
		\$528.98	SFO(525.1)	Hayward, CA(5)
	MSY(3.88)	\$362.48	SJC(358.6)	Hayward, CA(21)
		\$675.48	OAK(671.6)	Hayward, CA(4)
		\$594.31000000000001	SFO(687.6)	Hayward, CA(5)
		\$293.65999999999997	SJC(286.95)	Hayward, CA(21)
	GPT(6.71)	\$631.3100000000000	OAK(624.6)	Hayward, CA(4)
		\$6.71	Hayward, CA (Drive)(286.95)	
		\$286.95		

4.2 A* Search with Straight Line Heuristic

In addition to the above features, we thought that we could improve upon our algorithm by adding a heuristic component to our cost function. Across edges, we are mixing different modes of transportation which have different speeds. Additionally, costs for flying depends only on plane tickets where as costs for driving depends directly on the distance and miles per gallon of a vehicle. For this reason, we can not simply just use the distance as a heuristic but we need to first convert it to the proper units based on what we would like to minimize.

4.2.1 A* Experiment : Estimating Time based on Distance

Since commercial flights do not reach a speed faster than 600 mph, we tested adding the distance between two places divided by this speed. We found distance using the Haversine formula. If the latitude and longitude of a node n and the destination are (ϕ_1, ϕ_2) and (λ_1, λ_2) and r is the radius of the earth then,

$$d = 2r \arcsin \left(\sqrt{\sin^2 \left(\frac{\phi_2 - \phi_1}{2} \right) + \cos(\phi_1) \cos(\phi_2) \sin^2 \left(\frac{\lambda_2 - \lambda_1}{2} \right)} \right)$$

We then let

$$h(n) = \frac{d}{600} \text{ hours}$$

Using the previous example, we calculated the following costs for $h(n)$.

h(Amite)	3.03
h(BTR)	3.07
h(MSY)	3.09
h(IAH)	2.63
h(SFO)	0.11
h(LAX)	0.53
h(OAK)	0.09
h(Stockton)	0

In the end, we arrived at the same solution from 4.1.2.

4.2.2 Conclusion

When we use a heuristic based on the straight line distance, nodes that are closer to the goal node are more likely to get chosen. We noticed that this heuristic did not improve the performance. Suppose we want to go from A to B . There are two airports around A that have the same distance to A . One of the airports, say A_1 , is a small airport that lies along the way from A to B . The other airport, say A_2 , is a large airports that is out of the way. With this heuristic A_1 would get selected first. Since A_1 is a small airport, it does not have a direct flight towards the goal node. Having a layover would add a lot of time. The airport A_2 , on the other hand, does have a direct flight. Thus, it would be better to select A_2 first.

5 Software System Design and Implementation

We chose to use Java for our project in the IDE IntelliJ. We developed our GUI in JavaFX using the JFoenix design library. To compute the time and price of each edge we use many different Google APIs.

5.1 Search Classes

Given the latitude and longitude of the initial point (origin) and destination (goal), our search algorithm uses a few different classes to arrive at a solution. In 2 you can see the relevant fields and methods for each class.

1. **Problem.java** : stores information about the travel plans of the user
2. **Node.java** : represents a node in the search tree
3. **Search.java** : search algorithm logic
4. **FindAirports.java** : finds the n airports around a place

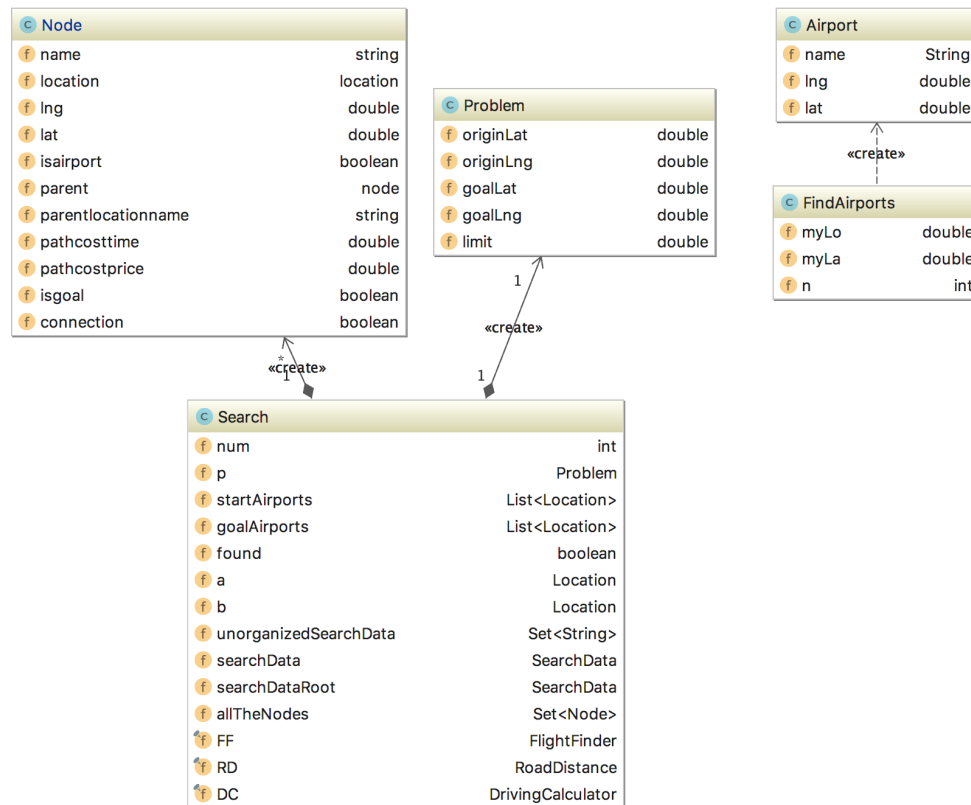


Figure 2: Search Classes

5.2 Map Utilities

5.2.1 Road Distance and Driving Calculator

`RoadDistance.java` gives simple distance, and driving time between two places (no driving directions though); a place can be coordinates, a zip, an address, or any string that would turn up a result in Google Maps. Uses Google Maps Distance Matrix API.

Main methods are:

- `getRoadDistance(String, String)`
- `getRoadTime(String, String)`
- `getRoadDistance(Location, Location)`
- `getRoadTime(Location, Location)`

`DrivingCalculator.java` figures out total price (gas + hotel) and duration (driving plus sleep) of a road trip. Main inputs are miles and hours (which you can get from `RoadDistance.java`).

Key constructor:

- `DrivingCalculator(double, double)`

Key methods:

- `calc()`,
- `calc(double, double)`

5.3 APIs

To gather data, we chose Google APIs for their ease of use specifically using HTTP transport and JSON parsing features. Below are the following APIs used and how they were used.

- QPX Express Airfare API : flight finder
- Google Maps Distance Matrix API : estimate travel time
- Google Maps Geocoding API : convert between addresses and latitude/longitude coordinates
- Google Maps Directions API : driving directions
- Google Places API Web Service : places autocomplete

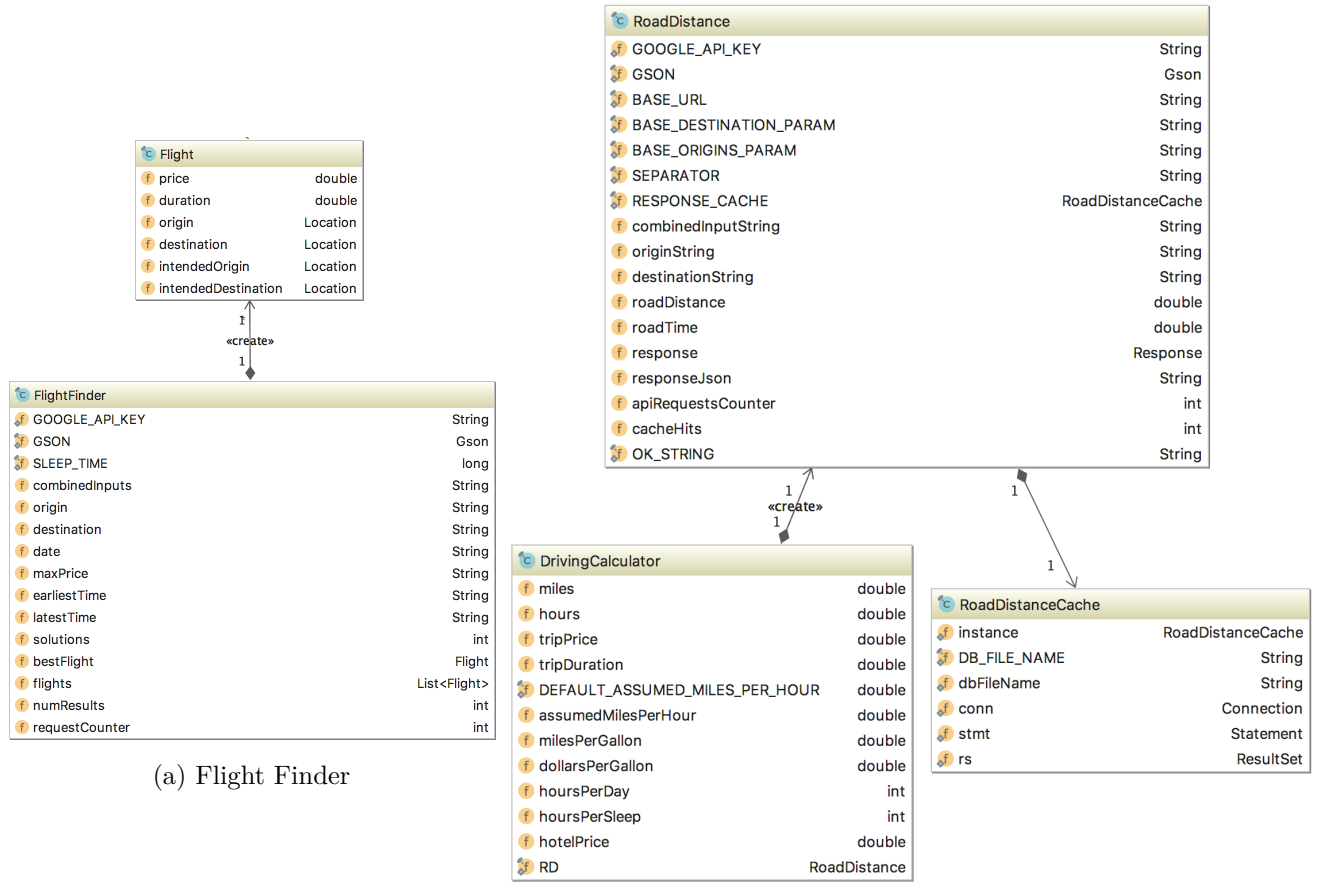


Figure 3: Map Utilities

5.4 Caching

Some of the APIs are quite slow, especially the QPX Express Airfare API to find flights. So to speed up our search time, we tried caching the data we found for future searches. We use two separate caches to make searches faster. One cache is used for road travel and one for flight. When we call the function used to determine the best route, it first searches the cache to see if the query has already been made in the past. If it has, it returns the result of the query. If this data is not stored, the API is called and the resulting distance is stored in the cache. This speeds up searching significantly over time because the cache will be able to be referenced more, avoiding costly calls to the API. The API calls take significantly longer than the cache calls, so it becomes faster and faster over time. In Figure 4 you can see a view of the physical data in the schema. Initially, we thought to use Bluemix for our database. We tried to integrate Bluemix but ran into complications passing information onto their server. It ended up being much simpler to manage our data locally using our caches and calling the API when necessary. Given more time and resources, we would ideally integrate a Bluemix database into our project and analyze the data.

The screenshot shows a SQLite database interface. On the left, a table named 'road_distance' is displayed with 15 rows. The columns are: origin_string, destination_string, road_distance, road_time, response, response_json, and hits. The data in the table is as follows:

	origin_string	destination_string	road_distance	road_time	response	response_json	hits
1	MSY Airport	IAH Airport	NULL	NULL	NULL	{destination_addr...	NULL
2	MSY	SFO	NULL	NULL	NULL	{destination_addr...	NULL
3	Miami International Airport	SJC	NULL	NULL	NULL	{destination_addr...	NULL
4	MSY	LFT	NULL	NULL	NULL	{destination_addr...	NULL
5	LFT	MSY	NULL	NULL	NULL	{destination_addr...	NULL
6	OAK	BTR	NULL	NULL	NULL	{destination_addr...	NULL
7	Baton Rouge, LA	Oakland, CA	NULL	NULL	NULL	{destination_addr...	NULL
8	New Orleans International Airport	Miami International Airport	NULL	NULL	NULL	{destination_addr...	NULL
9	BTR	LFT	NULL	NULL	NULL	{destination_addr...	NULL
10	70806	MSY	NULL	NULL	NULL	{destination_addr...	NULL
11	70806	Houston, TX	NULL	NULL	NULL	{destination_addr...	NULL
12	MSY	Denver, Colorado	NULL	NULL	NULL	{destination_addr...	NULL
13	MSY	DEN	NULL	NULL	NULL	{destination_addr...	NULL
14	DEN	MSY	NULL	NULL	NULL	{destination_addr...	NULL
15	MSY	Denver International Airport	NULL	NULL	NULL	{destination_addr...	NULL

On the right, the 'DB Schema' view is shown. It lists the following components:

- Tables (2):**
 - flight_finder_cache (CREATE T)
 - road_distance_cache (CREATE T)
- Indices (2):**
 - sqlite_autoindex_flight_finder_cache_1
 - sqlite_autoindex_road_distance_cac...
- Views (0)**
- Triggers (0)**

At the bottom of the interface, there are buttons for 'SQL Log', 'Plot', and 'DB Schema'.

Figure 4: SQLite database

6 Future Work

This application is restricted to traveling within the US. Other countries could be included to give the user the option to travel internationally. The only modes of transportation that are used are driving and flying. To give the user a more flexibility when traveling, other modes of transportation could be incorporated into this application such as walking, bicycling, taking the train or metro, and taking a ferry.

Additionally, after caching of a large amount of data our application could make certain predictions which improve our search algorithm. For example, instead of choosing the n nearest airports to add to our search tree, Watson Analytics predict feature could also choose an airport which may be slightly farther away but which may frequently have deals on flights.