Map Matching Benchmarks

This notebook is intended as a supplement to the Sendai Map notebook. This notebook implements the competing map matching algorithms and tests them against the map-matching-dataset for comparison.

In [2]:

```
# Data Input

df_track = db.read_text('map-matching-dataset/*track.geojson').map(json.loads
df_network_edges = db.read_text('map-matching-dataset/*arcs.geojson').map(jsor
df_network_nodes = db.read_text('map-matching-dataset/*nodes.geojson').map(js
df_gt = db.read_text('map-matching-dataset/*route.geojson').map(json.loads).m
```

In our case, our data is already fused. But often you will have several datasets with asynchronous data that you will have to fuse first. We implemented a barebones method in mm_utils to handle this; you can see an example of how to use it in '02a Data Pre-Processing'.

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In [3]:
```
# I wrote a utility function to do that, provided in mm_utils.

df_track_edges = df_track.map(mm_utils.point_to_traj)#, columns = {'timestamp
                                                       #  'altitude':'average',
                                                       #  'speed':'average',
                                                       #  'vertical accuracy':'
                                                       #  'horizontal accuracy'
                                                       #  'oops':'notavalidmeth
```

Now we demonstrate how we can work with several algorithms at once in a modular fashion.

First we initialize the simulators, to be later applied.

In [5]:

```python
from algorithms import fmm_bin
from fmm import FastMapMatchConfig

### Define map matching configurations

k = 8
radius = 0.003
gps_error = 0.0005

fmm_config = FastMapMatchConfig(k,radius,gps_error)
cfg_file = None


### Algorithm Implementation here, if not in separate .py file


###

sim1 = fmm_bin.FMM(cfg = fmm_config)
#sim2 = EKF.Sim(cfg = cfg_file)


## If you have the ground truth, load it here
ground_truth = db.read_text('map-matching-dataset/*route.geojson').map(json.l
```

In [6]:

```
## We will convert our Dask Bags to Dask Delayed objects so we can iterate ove
# Finally we will compute our results, and Dask will automatically paralleliz

gt = ground_truth.to_delayed()
te = df_track_edges.to_delayed()
tn = df_track.to_delayed()
ne = df_network_edges.to_delayed()
nn = df_network_nodes.to_delayed()
```

Now we are ready to run the simulator on a subsection (or all of) the data. Notice how easy it is to run algorithms in parallel-- all of the parallelization is handled by Dask Delayed, so even though our algorithm is only designed to handle one case at a time, it has already gained magnitudes of efficiency.

One small caveat-- even if your algorithm is technically 'independent', if you utilize python.os functions, you may run into I/O read/write errors. To circumvent this, use a dedicated library such as tempfile to systematically handle the temp file creation.

In [7]:
```python
## Let's see this!
sim1_results = []

n = 10

for i in range(n):
    sim1_results.append(dask.delayed(sim1.run)(te[i],
                                               tn[i],
                                               ne[i],
                                               nn[i],
                                               return_results=True))

from dask.distributed import Client, LocalCluster



cluster = LocalCluster()  # Launches a scheduler and workers locally
client = Client(cluster)  # Connect to distributed cluster and override defau
client.restart()
# This is the best scheduler to use when doing I/O operations (which FMM requ


sim1_results[:3]
sim1_results = dask.compute(*sim1_results, scheduler='sync')

#sim1.run(input_nodes = df_nodes, input_edges = df_edges, network_nodes = netw
#sim1.results
#sim1_results
```

```
2022-07-15 00:18:23,895 - distributed.diskutils - INFO - Found stale
```

Now we iterate through our results, and evaluate it using the build-in evaluation method in mm_utils.

In [43]:

```
errors = []
for i in range(len(sim1_results)):
#    errors.append(dask.delayed(mm_utils.evaluate)(sim1_results[i],gt[i], mat
# For whatever reason, delayed isn't working here, so I'm just going to do th
    errors.append(mm_utils.evaluate(sim1_results[i],
                                    gt[i].compute()[0],
                                    matchid = "index")) # A more standard mat

#errors = [dask.compute(*errors)]

#sim2.run(input_nodes = df_nodes, input_edges = df_edges, network_nodes = net
#pred_nodes, pred_edges = sim2.results
# I did implement plot() and evaluate() for sim2
# But for demonstration, I will use mm_utils, as some programmers may choose
#sim2.plot()
#sim2.evaluate()
#mm_utils.plot(network, df_nodes.append(df_edges), sim2.results())
#mm_utils.evaluate(sim2.results(), ground_truth, match='index'
```

In [49]:

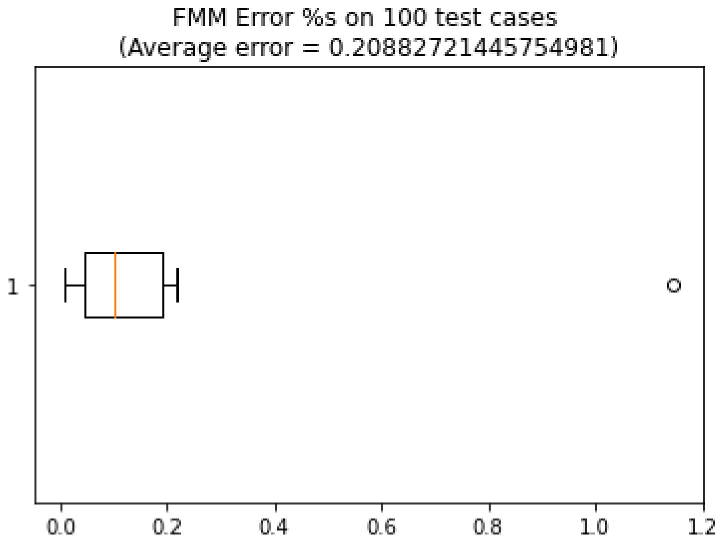
```python
fig = plt.figure(1)
plt.boxplot(errors,vert=False)
plt.title('FMM Error %s on '
          + str(n)
          + ' test cases \n(Average error = '
          + str(np.average(errors)) + ')')
plt.show()
```

Out[49]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x7ff875d6a740>,
  <matplotlib.lines.Line2D at 0x7ff875d6aa10>],
 'caps': [<matplotlib.lines.Line2D at 0x7ff875d6ace0>,
  <matplotlib.lines.Line2D at 0x7ff875d6afb0>],
 'boxes': [<matplotlib.lines.Line2D at 0x7ff875d6a470>],
 'medians': [<matplotlib.lines.Line2D at 0x7ff875d6b280>],
 'fliers': [<matplotlib.lines.Line2D at 0x7ff875d6b3d0>],
 'means': []}
```

Out[49]:

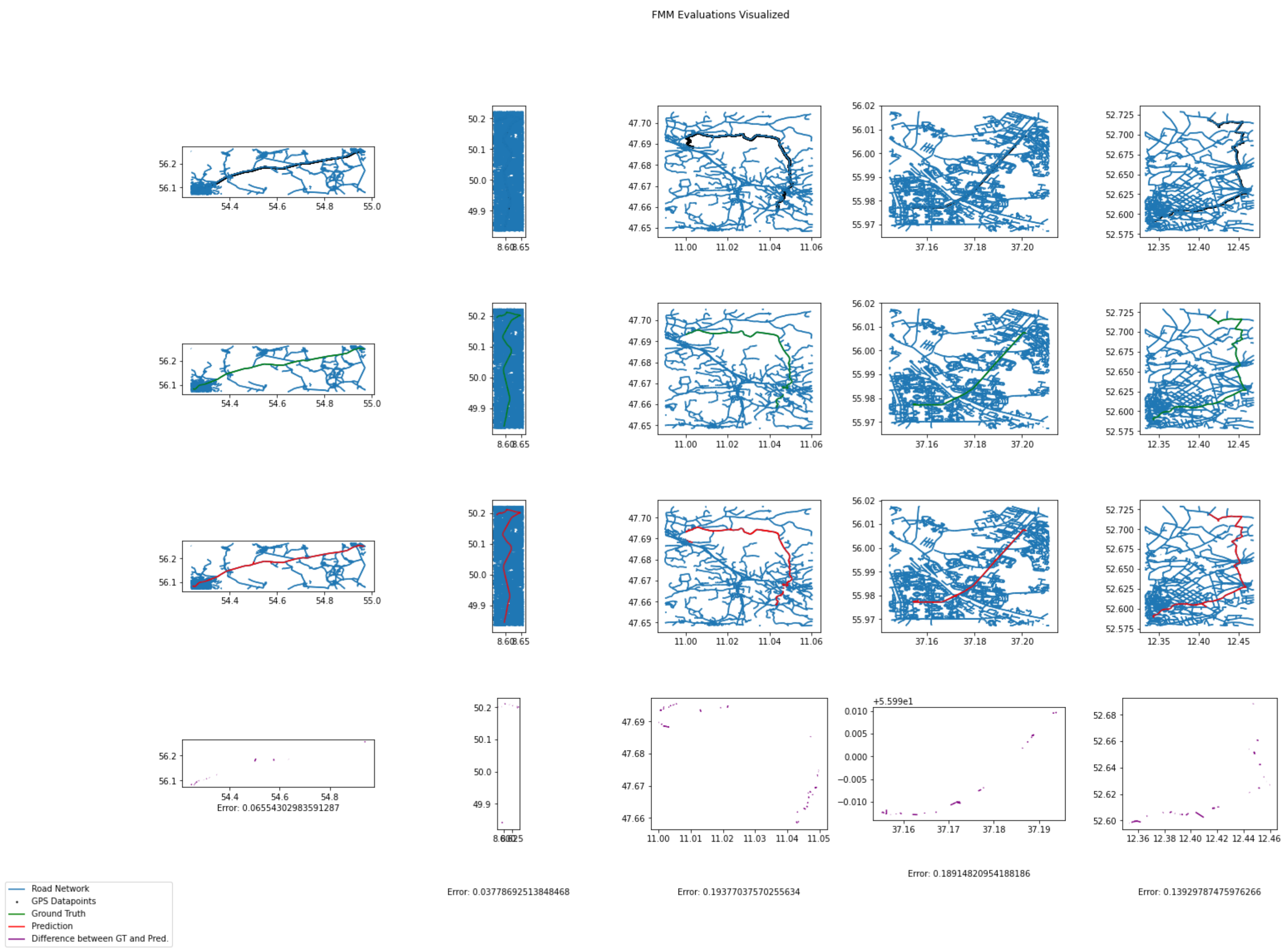
```
Text(0.5, 1.0, 'FMM Error %s on 100 test cases \n(Average error = 0.2
0882721445754981)')
```


FMM Error %s on 100 test cases
(Average error = 0.20882721445754981)
1
0.0
0.2
0.4
0.6
0.8
1.0
1.2

Overall, FMM seems to handle itself okay, with the exception of one huge outlier!

(Note-- having an error above 100% is not a bug; the standard error formula is not upper-bounded, despite being a percentage)

Let's see a few examples of our results.


FMM Evaluations Visualized
Error: 0.06554302983591287
Error: 0.03778692513848468
Error: 0.19377037570255634
Error: 0.18914820954188186
Error: 0.13929787475976266
Road Network
GPS Datapoints
Ground Truth
Prediction
Difference between GT and Pred.