Imputing jumps in GPS location

Don Li 08/06/2020

What are we doing?

```
load( "../../dataset/all_SNG.RData" )
source( "utility.R" )
```

If we look at the speeds, we can often find trips where there is -1 speed between trips.

```
# Number of trips with invalid speed
trips_with_bad_pings = all_data[ , any( speed < 0 ), by = "trj_id" ]
trips_with_bad_pings[ , sum(V1) ]</pre>
```

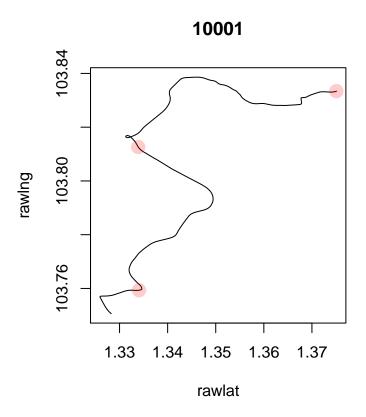
```
## [1] 10092
```

We can look at the distance associated with these negative speeds. We can see that the steps with negative speed tend to be higher on average than steps with positive speed. Clearly, this is wrong, and these negative speeds represent some kind of error. Note that 0 is excluded because 0 is valid on iOS but not Android.

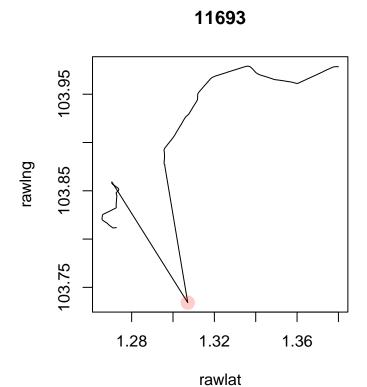
```
all_data[ speed < 0, summary( H_dist ) ]</pre>
##
       Min.
             1st Qu.
                       Median
                                   Mean
                                         3rd Qu.
                                                     Max.
    0.00000 0.01358
                      0.01911
                                0.03252
                                         0.02363 20.29763
all_data[ speed > 0, summary( H_dist ) ]
##
             1st Qu.
                       Median
                                        3rd Qu.
       Min.
                                   Mean
                                                     Max.
    0.00000 0.01276 0.01841 0.01801 0.02224 18.19138
```

Visualise

Sometimes the negative speed is a benign thing, such as in the trip below. The red points are where the speed was less than 1.



NULL



NULL

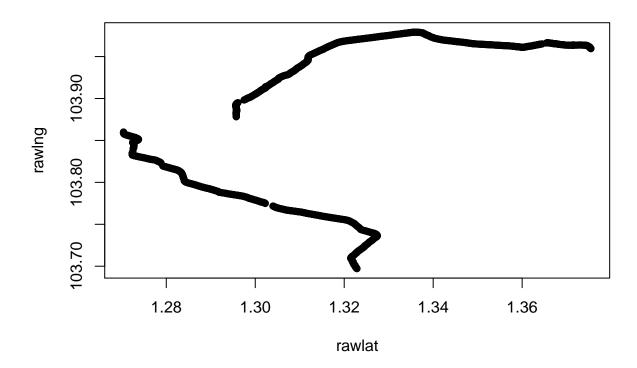
Conclusion

I do not think the negative speed in itself is worrying. But it could be symptomatic of something worse, like a jump in the GPS pings.

Analyse trips with big jumps

An example:

```
all_data[ trj_id == 10011, {
    plot(rawlat, rawlng, pch = 16, main = trj_id[1])
    } ]
```



NULL

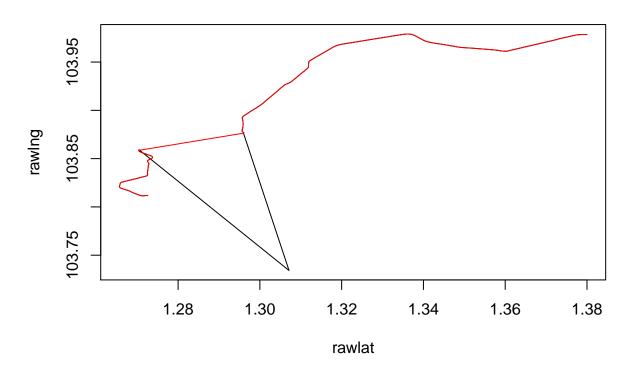
This one seems fine. It looks like their GPS stopped working for a bit, or they went into a tunnel or something. So, I think the cases where we might worry is when there are two points with very large distances. In the example plotted previously:

```
all_data[ trj_id == 11693 ][ which(speed < 0) + -2:2 ]
##
      trj_id osname
                        rawlat
                                                                  date_ weekday hour
                                 rawlng
                                             speed
       11693 android 1.270380 103.8591 18.667429 2019-04-18 22:43:11
                                                                            Thu
                                                                                  22
       11693 android 1.270421 103.8592 18.687794 2019-04-18 22:43:12
                                                                                  22
                                                                            Thu
       11693 android 1.307128 103.7342 -1.000000 2019-04-18 22:44:28
                                                                                  22
## 3:
                                                                            Thu
                                                                                  22
       11693 android 1.295993 103.8763
                                         3.303370 2019-04-18 22:50:43
                                                                            Thu
##
       11693 android 1.295996 103.8764
                                         4.502514 2019-04-18 22:50:44
                                                                            Thu
                                                                                  22
##
      is_weekend rush_hour
                                  H_{dist}
                                              H_dist2 time_diff
## 1:
           FALSE
                             0.018720461
                                          0.01866304
                                                              1
## 2:
           FALSE
                             0.018390294
                                          0.01782980
                                                              1
## 3:
           FALSE
                         No 14.501549257 13.95153667
                                                             76
                         No 15.867322948 15.82567291
                                                            375
## 4:
           FALSE
## 5:
           FALSE
                             0.003442773 0.00342823
                                                              1
```

An imputed journey for 11693 is shown below. We impute by finding points where there are two steps larger than 5 in a row. The black line is the original, the red is the one with the imputed point.

```
test_data = all_data[ trj_id == 11693 ]
two_window_threshold = function( x, threshold ){
    (x > threshold) & (c( x[-1], F ) > threshold)
}
```

```
test_data[ , c( "rawlat", "rawlng" ) := {
    missing_dist = which( two_window_threshold( H_dist, 5 ) )
    for ( missing in missing_dist ){
        neighbours = missing -5:5
        around_lat = rawlat[ neighbours ]
        around_lng = rawlng[ neighbours ]
        interpolate_lat = mean( around_lat, na.rm = T )
        interpolate_lng = mean( around_lng, na.rm = T )
        rawlat[ missing ] = interpolate_lat
       rawlng[ missing ] = interpolate_lng
   list( rawlat, rawlng )
    } ]
test_data[ , H_dist := c( 0, haversine(rawlat, rawlng) ) ]
all_data[ trj_id == 11693,{
    plot( rawlat, rawlng, type = "1",
        main = trj_id[1])
    } ]
## NULL
test_data[ , {
    lines( rawlat, rawlng, type = "1", col = "red" )
} ]
```



NULL

And the distances seem more reasonable with the imputed values.

```
# Crow flies distance
all_data[ trj_id == 11693, haversine( rawlat[c(1,.N)], rawlng[c(1,.N)] ) ]

## [1] 22.08126

# Path distance
all_data[ trj_id == 11693, sum( H_dist, na.rm = T ) ]

## [1] 55.84373

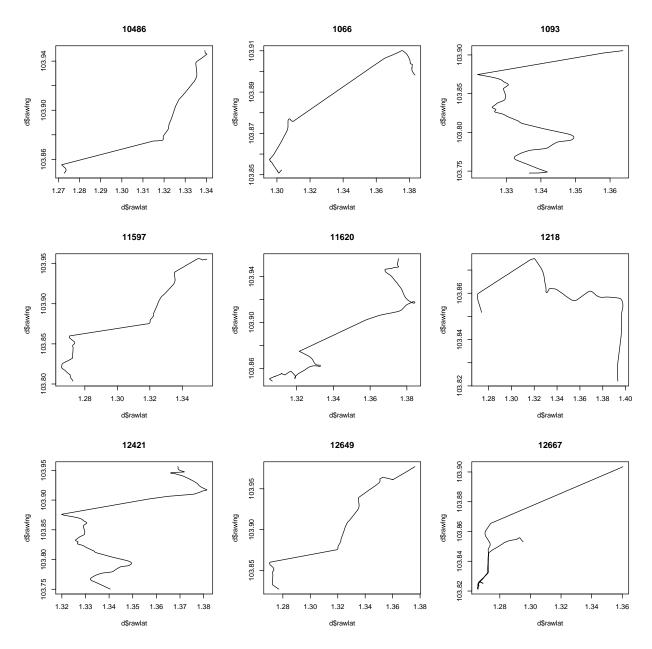
# Path with imputation
test_data[ , sum(H_dist) ]

## [1] 29.02173
```

Do this with the rest of the data:

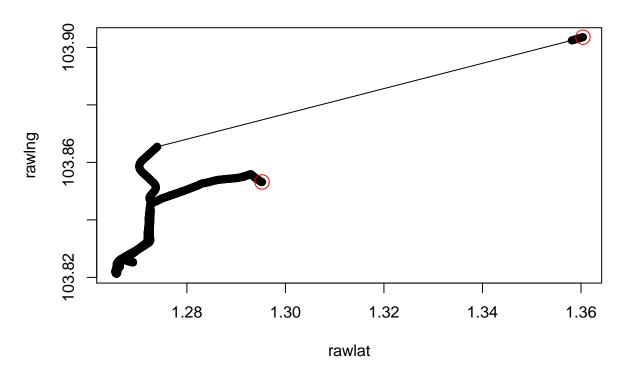
```
all_data[ , c( "rawlat", "rawlng" ) := {
   missing_dist = which( two_window_threshold( H_dist, 5 ) )
   for ( missing in missing_dist ){
       neighbours = missing -5:5
        around_lat = rawlat[ neighbours ]
        around_lng = rawlng[ neighbours ]
        interpolate_lat = mean( around_lat, na.rm = T )
        interpolate_lng = mean( around_lng, na.rm = T )
       rawlat[ missing ] = interpolate_lat
       rawlng[ missing ] = interpolate_lng
   list( rawlat, rawlng )
}, by = "trj_id" ]
all_data[ , c("H_dist", "H_dist2") := {
   h_dist = haversine( rawlat, rawlng )
   h1 = c(0, h_dist)
   h_dist2 = haversine( rawlng, rawlat )
   h2 = c(0, h_dist2)
   list( h1, h2 )
}, by = "trj_id" ]
```

Try to find some trips with big jumps.



Examnine 12667. Seems okay. GPS probably just broke at the start.

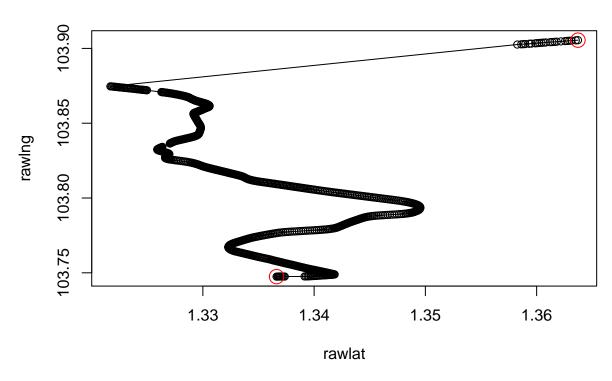
```
par( mfrow = c(1,1 ))
trip = 12667
all_data[ trj_id == trip, {
    plot( rawlat, rawlng, main = trj_id[1], type = "o" )
    points( rawlat[c(1,.N)], rawlng[c(1,.N)], col = "red", cex = 2 )
} ]
```



NULL

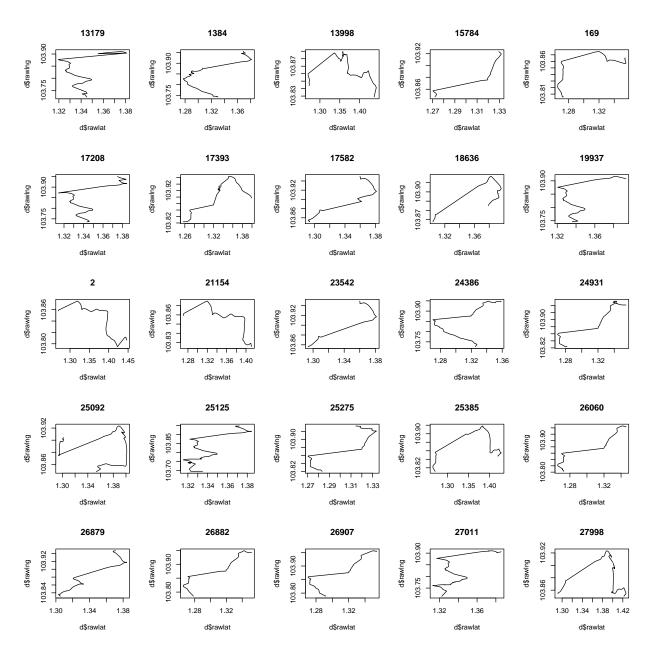
Examnine 1093 Seems okay. GPS probably just broke at the start.

```
par( mfrow = c(1,1 ))
trip = 1093
all_data[ trj_id == trip, {
    plot( rawlat, rawlng, main = trj_id[1], type = "o" )
    points( rawlat[c(1,.N)], rawlng[c(1,.N)], col = "red", cex = 2 )
} ]
```



NULL

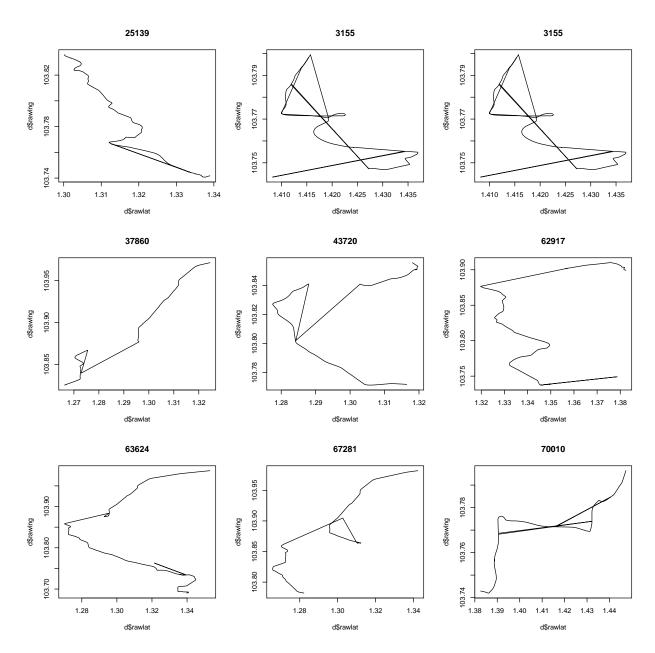
Try again:



Seems okay.

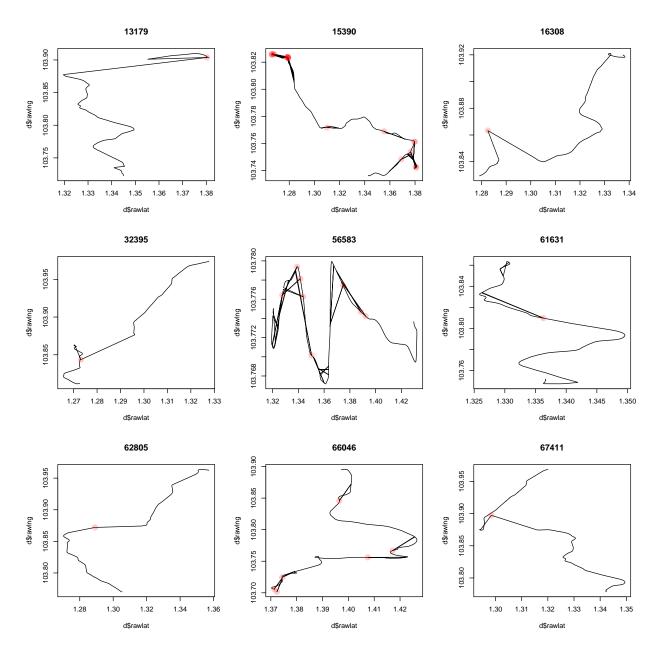
Round 2

Try detecting bad jumps with a smaller threshold



Set new threshold for jumps to 3.

Round 3



Went up to two and that seemed good enough. Still a couple of weird ones, but a pretty small minority.

Conclusions:

For cleaning the data, we will interpolate the coordinates of points where that point and the next point have a large distance from the previous point. This represents the situation where there is one stray ping somewhere. The distance we will use is 2km (Haversine).