Tracking Community Mobility:
An R Program for Cleaning and Creating Constructs from GPS Data

1 Photo of child walking a dog on a sidewalk with a light shining down only on them

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Suggested Citation: Brusilovskiy, E., Jaraha, E., Klein, L.A., & Salzer, M.S. (2020). Tracking Community Mobility: An R Program for Cleaning and Creating Constructs from GPS Data. Temple University Collaborative on Community Inclusion.

Acknowledgement: The authors are affiliated with the Temple University Collaborative on Community Inclusion of Individuals with Psychiatric Disabilities. The contents of this document were developed under a grant from the National Institute on Disability, Independent Living and Rehabilitation Research (NIDILRR; Grant Number 901F0065-02-00; Salzer, PI). However, the contents do not necessarily represent the policy of the U.S. Department of Health and Human Services, and endorsement by the Federal government should not be assumed.

Cover photo from https://pixabay.com/photos/person-dog-urban-lamp-post-child-498197/ (Free for commercial use)

For technical assistance and support in using this document and approach please contact Eugene Brusilovskiy at eugeneby@temple.edu.

INTRODUCTION

Global positioning systems (GPS) technology offers one promising approach for expanding measurement of health through a greater understanding of community mobility and participation and physical activity. While GPS technology is not new, decreased costs and increased accessibility have made it a promising method of data collection, and a growing body of research from around the world demonstrates the potential utility of GPS technology.

However, current published studies provide limited detail on their analytical approaches, which may be problematic, as GPS data are numerous and complex. For example, data collection at one-minute intervals could yield 1440 time-stamped data points with latitude and longitude values over the course of a 24 hour period, and using these data in a meaningful way is very complicated. However, there are often inaccuracies and errors associated with GPS data, due to factors including, but not limited to, atmospheric conditions, satellite and receiver errors, and multipath errors (i.e., the GPS signal reflecting off tall objects before it reaches the receiver). Certain types of error may be reduced by post-processing GPS data, however these corrections aren't helpful with receiver or multipath errors, with the latter being especially likely in urban environments (Trimble, 2004)[1]. Error also depends on the GPS device that is being used.

Finally, there has been little discussion about how missing data are addressed. As mentioned above, GPS data collection is sensitive to weather (e.g., Hillier, 2008)[2] and satellite access, which can be blocked when indoors (e.g., Harris et al., 2010)[3], and instead of obtaining an incorrect location at certain time points, data may be absent altogether. Human factors, such as not keeping the tracking device charged, can also create missing data. Therefore, missing data are common in such data collection approaches, and require attention.

All those issues notwithstanding, numerous studies have used GPS to create a wide range of constructs related to community mobility, participation and physical activity. This is often tedious task, as it relies on first cleaning the data and then manually creating these constructs.

This program aims to automate these tasks, and to do them for all study participants at once. First, it provides a thorough cleaning of each participant's GPS data, and

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[1] Trimble Navigation Limited, 2004. Why Postprocess GPS Data? Mapping and GIS White Paper Trimble Navigation Limited, Westminster, CO.
[2] Hillier, A., 2008. Childhood overweight and the built environment: making technology part of the solution rather than part of the problem. Ann. Am. Acad. Political Soc. Sci. 615 (1), 56e82.
[3] Harris, F., Sprigle, S., Sonenblum, S.E., MSaurer, C.L., 2010. The participation and activity measurement system: an example application among people who use wheeled mobility devices. Disabil. Rehabil. Assist. Technol. 5 (1), 48e57.

addresses common problems, such as the elimination of duplicate points, smoothing of outliers, and imputation of missing data through linear interpolation. Second, it creates a number of constructs from GPS data, doing additional data cleaning and imputation in the process.

These constructs include:

1) Total number of destinations over the course of the study period

2) Total number of unique destinations

3) Total number of non-home destinations

4) Total number of destinations within 1/2 mile of home

5) Total number of destinations within 1 mile of home

6) Activity space area

7) Total distance traveled

8) Amount of time spent at home

9) Amount of time spent outside of home

10) Amount of time spent in transit

11) Amount of time spent at other destinations

12) Total number of non-missing days (i.e., days with fewer than 50% of the data after cleaning and imputation)

The program was designed to work with GPS data that have been collected with a cellular phone using an app called AccuTracking (www.accutracking.com), however it will work with GPS data collected using other apps and stand-alone trackers, as long as the data have been collected at one minute intervals and have the date-time stamp and latitude and longitude coordinates in decimal degrees.

PACKAGES AND CUSTOM FUNCTIONS

This program uses the following packages and extensions:

```
#rm(list=ls(all=TRUE))

pckgs <- c("geosphere", "dplyr", "zoo","rgdal","dbscan","cluster","RColorBrewer", "geo
metry","grDevices","sp")

#install.packages(pckgs)

library(geosphere)    # distVincentyEllipsoid

library(dplyr)        # left_join, groupby, between

library(zoo)          # na.approx

library(rgdal)

library(sf)           # project

library(dbscan)       # dbscan

library(cluster)      # silhouette

library(RColorBrewer) # colorRampPalette

library(geometry)     # polyarea

library(grDevices)    # chull

library(sp)           # polygon

library(Jmisc)        # Add column

memory.limit(size=100000)
```

This file contains custom extensions to be run in conjunction with the program:

```
source("T:\\functions14days.r")
```

In the interest of keeping order in variable sheets, these variables are initialized at the very beginning of each run of this program. These reset each sheet to a blank frame and the future analyses fill these variables.

```
TimeSheet <- data.frame(matrix(ncol = 7, nrow = 0))

DistanceSheet <- data.frame(matrix(ncol = 4, nrow = 0))

OtherSheet <-data.frame(matrix(ncol = 19,nrow = 0))

TotalMissing <-data.frame(matrix(ncol = 2,nrow = 0))

TotalFrequencies<-data.frame(matrix(ncol=4,nrow=0))

colnames(TotalFrequencies)<- c("ID","WithinHalfMile","WithinFullMile","GreaterThanMile
")

VarOut <-data.frame(matrix(ncol=23,nrow=0))
```

HOME ADDRESSES

Before we proceed any further, we need to take the .csv file with all the geocoded home addresses (presented as latitude and logitude), and project it to the same coordinate system that we used earlier. Here, we are using the same options as in the project_coordinates() function.

```
#CSV file containing geocoded home locations (i.e., latitude and longitude coordinates
of geocoded addresses)

HomeAll <- read.csv('T:\\Addresses for R.csv', header = TRUE, sep = ",")


out_Home = st_as_sf(HomeAll, coords=c(2,3), crs=4269)    #column 2: Longitude (X); Col
umn 3: Latitude (Y)

out2_Home <- st_transform(out_Home, 6564)

Coord_Home <- as.data.frame(st_coordinates(out2_Home))

Projected_Home <- as.data.frame(append(HomeAll, Coord_Home))

Projected_Home$Long_proj <- Projected_Home$X.1

Projected_Home$Lat_proj <- Projected_Home$Y.1

Projected_Home <- Projected_Home[-c(2:5)]                          #Keeping ID and pro
jected coordinates only!
```

IMPORTING AND CLEANING THE GPS DATA

First, we define directory and input path information. Specifically, each of the participants has GPS data saved as a .csv file. The format of the file names is "Participant # Cleaned.csv", where the # is the 4-digit ID of each participant. Each of the files contains, among other variables, 1) the Time Stamp, 2) Latitude, and 3) Longitude of each GPS point.

Then, after the data have been imported, there are three steps to data cleaning: 1) deduplication of data, 2) smoothing of outliers, and 3) imputing missing points between observed points within 20 minutes apart. Each process is explained in detail below.

Deduplication

Each cell phone recorded longitude/latitude readings at approximately 60 second intervals. There were some occasions during this study, however, where readings may have occurred in slightly fewer than 60 second intervals, such as 59 or 58 seconds apart. In these cases, multiple latitude/longitude readings may have been made during the same minute of time. For example, one reading may have taken place at 1:33 PM on the 1st second and 1:33 PM on the 59th second. Since we are considering only one reading per minute in this study, the first observation (1:33:00) is retained and the second observation (1:33:58) is removed from the analysis. This deduplication did not result in any significant loss of participant tracking data.

Here is an example of the data before deduplication:

1	Date	Long	Lat
8	10/25/2011 13:01	-75.15544	39.98627
9	10/25/2011 13:17	-75.158	39.98344
10	10/25/2011 13:21	-75.15709	39.98102
11	10/25/2011 13:25	-75.15765	39.9779
12	10/25/2011 14:03	-75.16709	39.97892
13	10/25/2011 14:16	-75.15765	39.9779
14	10/25/2011 14:22	-75.16709	39.97892
15	10/25/2011 14:22	-75.16237	39.97841
16	10/25/2011 14:22	-75.15765	39.9779
17	10/25/2011 14:36	-75.15911	39.97798

After the deduplication, only the first of these points was kept, as can be seen below.

1	Date	Long	Lat
65	10/25/2011 14:17	-75.15922333	39.97807
66	10/25/2011 14:18	-75.16079667	39.97824
67	10/25/2011 14:19	-75.16237	39.97841
68	10/25/2011 14:20	-75.16394333	39.97858
69	10/25/2011 14:21	-75.16551667	39.97875
70	10/25/2011 14:22	-75.16709	39.97892
71	10/25/2011 14:23	-75.16652	39.97885286
72	10/25/2011 14:24	-75.16595	39.97878571
73	10/25/2011 14:25	-75.16538	39.97871857
74	10/25/2011 14:26	-75.16481	39.97865143

Smoothing Outliers

Some points may have resulted from glitches in cellular signal which placed individuals very far from their actual locations. Although these errant observations were rare occurrences, removing the outlier points was a necessary step in order to accurately calculate the different GPS variables, especially distance traveled. In these occasions, the outlier longitude and latitude point was recalculated as the average of the points immediately before and after the outlier.

Before outlier smoothing, we see a point which had incorrect (or truncated) coordinates:

1	Date	Long	Lat
43	10/25/2011 21:38	-75.2162	39.95601
44	10/25/2011 21:39	-75.21808	39.95389
45	10/25/2011 21:40	-75.21884	39.95043
46	10/26/2011 9:27	-75.1585	39.97835
47	10/26/2011 11:23	-75.15872	39.97856
48	10/26/2011 14:55	-75.15947	39.97761
49	10/26/2011 15:16	-75.15795	39.97911
50	10/26/2011 20:17	-75.21892	39.95029
51	10/26/2011 20:18	-75	39
52	10/26/2011 20:19	-75.21898	39.95026

After outlier smoothing, the data point at 20:18 (8:18 PM) has latitude and longitude coordinates which are averages of the coordinates of the 8:17 PM and 8:18 PM data points.

1	Date	Long	Lat
191	10/26/2011 15:12	-75.15823952	39.97882429
192	10/26/2011 15:13	-75.15816714	39.97889571
193	10/26/2011 15:14	-75.15809476	39.97896714
194	10/26/2011 15:15	-75.15802238	39.97903857
195	10/26/2011 15:16	-75.15795	39.97911
196	10/26/2011 20:17	-75.21892	39.95029
197	10/26/2011 20:18	-75.21895	39.950275
198	10/26/2011 20:19	-75.21898	39.95026
199	10/26/2011 20:20	-75.218985	39.950295
200	10/26/2011 20:21	-75.21899	39.95033

Imputing Missing Points

During this study, phones may have had brief signal interruptions when participants went inside buildings, underground subway stations, or tunnels. The phones would not be able to record latitude and longitude points while they lost satellite signal. If there was a gap in the data which was 20 or fewer minutes between consecutive points, missing data were imputed through linear interpolation.

For example, before the linear interpolation, the highlighted points below are three minutes apart.

1	Date	Long	Lat
129	10/27/2011 0:46	-75.219	39.95014
130	10/27/2011 0:47	-75.21901	39.95014
131	10/27/2011 0:48	-75.21901	39.95013
132	10/27/2011 0:49	-75.21901	39.95013
133	10/27/2011 0:50	-75.21901	39.95013
134	10/27/2011 0:53	-75.21902	39.95013
135	10/27/2011 0:54	-75.21902	39.95013
136	10/27/2011 0:55	-75.21901	39.95013
137	10/27/2011 0:56	-75.21901	39.95013
138	10/27/2011 0:57	-75.21901	39.95014

After the linear interpolation, two new points at 0:51 and 0:52 were created. Their coordinates were weighted averages of the coordinates at 0:50 and 0:53.

1	Date	Long	Lat
370	10/27/2011 0:46	-75.219	39.95014
371	10/27/2011 0:47	-75.21901	39.95014
372	10/27/2011 0:48	-75.21901	39.95013
373	10/27/2011 0:49	-75.21901	39.95013
374	10/27/2011 0:50	-75.21901	39.95013
375	10/27/2011 0:51	-75.21901333	39.95013
376	10/27/2011 0:52	-75.21901667	39.95013
377	10/27/2011 0:53	-75.21902	39.95013
378	10/27/2011 0:54	-75.21902	39.95013
379	10/27/2011 0:55	-75.21901	39.95013

```
# set working directory
setwd("T:\\Data")


# list of paths to participant data files
data_path_list <- list_data_paths("Participant [[:digit:]]{4} Cleaned.csv", FALSE)
set.seed(1234)


for (path1 in data_path_list[2]){         # If we want it to loop, we write data_path_
list[1:118]
    # participant number and directory name
    participant_number <- substring(path1,15,18)
    #dir_name <- dirname(sub('.','',(sub('.','',path1))))
    dir_name <- dirname(path1)
    #Importing the Data
    data <- read.csv(path1, stringsAsFactors = FALSE)
    cat("\n\n", "Importing Participant Data: ",path1)
    nrow_a <- nrow(data)


    #Deduplicating the Data
    data_x <- data[!duplicated(data[c("Date")]),]
    cat("\n\n", "number of duplicate records dropped:", nrow_a-nrow(data_x))   # cat i
s a printing function


    #Smoothing Outliers
    data_x <- id_subset(df="data_x","Date","Long","Lat")
```

```
    data_x <- as_POSIXct()

    data_x <- time_gap_minutes()

    data_x$cum_time <- cumsum(data_x$time_gap)

    #This uses Vincenty's Ellipsoid Distance, and reports in meters. No projection nee
ded.

    data_x <- distance_meters()

    data_x <- smooth_outliers()


    #Imputing Missing Points

    attributes(data_x$Date)$tzone<- "America/New_York"

    start_date <- data_x[1,"Date"]

    # define end date

    start_time = "00:00:00"

    start_date1 <- paste(format(start_date, "%y/%m/%d"), start_time)


    start_date <- strptime(start_date1, "%y/%m/%d %H:%M:%S")

    attributes(start_date)$tzone <- "America/New_York"


    end_date <- (start_date+86400*14)-1        #Daylight savings time can shift end da
te by an hour


    #end_datepart <- format(end_date, '%y/%m/%d')

    #When Daylight Savings time starts, last time stamp ends up being 23:00 or 23:01,
so we change it to 23:59

    #end_time <- "23:59:00"

    #end_time <- paste(end_datepart, end_time)

    #end_time1 <- strptime(end_time, "%y/%m/%d %H:%M:%S")

    #attributes(end_time1)$tzone <- "America/New_York"


    #When Daylight Savings time ends, we want to make sure that we don't have an extra
day in there due to changing the

    #end_time to 23:59:00, so we check to see if the difference between end_time1 and
start_date is more than (14 days + an     #hour and change). If so, we shift the end_t
ime1 date back by a day

    #if (end_time1 > start_date + (86400*14 + 3700)) {end_time1 = end_time1 - 86000}


    #create dataframe

    date_time <- data.frame("Date" = seq.POSIXt(start_date,end_date,"min",
                                               tz="America/New_York"))
```

```
    date_time <- left_join(date_time, data_x, by=c("Date"="Date"))

    print("Imputing longitude and latitude where time_gap <= 20")
    date_time <- impute("date_time","Long","Lat")
    nrow_a <- nrow(date_time)

    date_time$Long <- replace(date_time$Long, is.na(date_time$Long), 0)

    date_time <- date_time[which(date_time$Long<0),]



    cat("\n\n", "Number of observations missing after imputation: ", nrow_a-nrow(date_
time))
    date_time <- time_gap_minutes(df="date_time")
    date_time$cum_time <- cumsum(date_time$time_gap)
    date_time <- distance_meters(df="date_time")
    file_name <- paste("Participant",participant_number,"Imputed.csv")
    file_path <- paste(getwd(),dir_name,file_name,sep="/")

    #Exporting Cleaned Data
    cat("\n\n", "Writing csv of imputed dataset:", file_path)
    write.csv(date_time,file_path, row.names = FALSE)
}
##
##
##  Importing Participant Data:  ./Participant 1002/Participant 1002 Cleaned.csv
##
##  number of duplicate records dropped: 150[1] "0 outliers smoothed"
## [1] "Imputing longitude and latitude where time_gap <= 20"
##
##
##  Number of observations missing after imputation:  3700
##
##  Writing csv of imputed dataset: T:/./Participant 1002/Participant 1002 Imputed.csv
```

We can see the variables that are part of the exported .csv file:

```
head(date_time)
##                  Date ID      Long      Lat time_gap cum_time  distance
## 1 2020-01-03 00:00:00  1 -75.17187 39.97097        0        0  0.000000
## 2 2020-01-03 00:01:00  2 -75.17191 39.97110        1        1 14.833408
## 3 2020-01-03 00:02:00  3 -75.17187 39.97107        1        2  4.772099
## 4 2020-01-03 00:03:00 NA -75.17184 39.97107        1        3  2.990046
## 5 2020-01-03 00:04:00  4 -75.17180 39.97107        1        4  2.990046
## 6 2020-01-03 00:05:00 NA -75.17185 39.97113        1        5  7.691672
```

IDENTIFICATION OF DESTINATIONS THROUGH ST-DBSCAN

ST-DBSCAN is a spatiotemporal data mining algorithm that takes into consideration the spatial and temporal proximity of GPS points to identify spatiotemporal clusters, or destinations. An extension of the DBSCAN clustering algorithm, ST-DBSCAN has three parameters: time, distance, and minimum number of points. Roughly speaking, this means that when there are at least 10 points which are all within 200 meters and 20 min of each other, the individual was in a cluster, or at a destination (Brusilovskiy, Klein, Salzer, 2016)[4].

First, we define the directory and input path information.

Then, we run a for loop which imports the cleaned files. The loop does a few commands for each participant:

1. It projects the coordinates from decimal degrees to meters.

2. It runs ST-DBSCAN with the aforementioned parameters and saves the results.

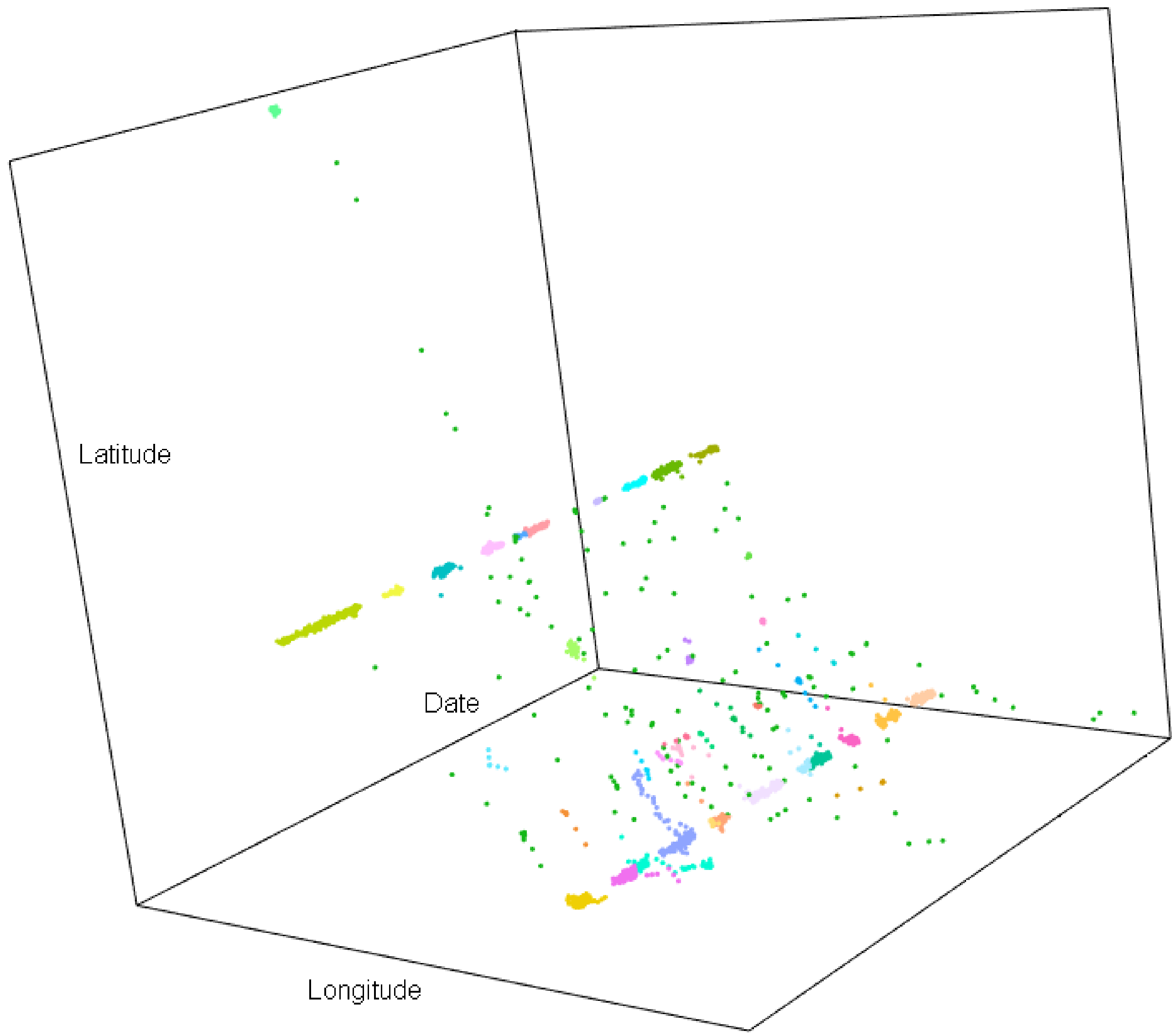
```
setwd("T:\\Data")

data_path_list2 <- list_data_paths("Participant [[:digit:]]{4} Imputed.csv",TRUE)

out_dir <- "T:\\Data"

library(ggplot2)

##

## Attaching package: 'ggplot2'

## The following object is masked from 'package:Jmisc':

##

##     %+%

library(randomcoloR)

library(rgl)

options(scipen = 999)

set.seed(1234)

memory.limit(size=100000)

## [1] 100000

for (path2 in data_path_list2[2]){      # If we want it to loop, we write data_path_li
st2[1:118]

    cat("\n\n", "Importing Participant Data:",path2)
```

[4] Brusilovskiy, E., Klein, L. A., & Salzer, M. S. (2016). Using global positioning systems to study health-related mobility and participation. Social Science & Medicine, 161, 134-142.

```
    data_x <- read.csv(path2, stringsAsFactors = FALSE, colClasses = c("Date" = "POSIX
ct"))

    #Projecting coordinates from decimal degrees to meters
    cat("\n\n", "Projecting coordinates")

    data_x <- project_coordinates()
    data_x <- subset(data_x,select = -c(X,Y))

    #Setting the ST-DBSCAN Parameters and running ST-DBSCAN
    #Define output file name and path
    param <- data.frame(eps=200,eps2=20,minpts=10)
    participant_number <- substring(path2,15,18)
    file_name <- paste("Participant",participant_number,"Imputed STDBSCAN",
                       param$eps,param$eps2,paste(param$minpts,".csv",sep=""))
    particip <- paste("Participant", participant_number, sep=" ")
    file_path <- paste(out_dir, particip, file_name,sep="\\")

    #Run ST-DBSCAN
    print(paste("Running ST-DBSCAN with the following parameters: Eps = ", param$eps,
", Eps2 =", param$eps2, ", minpts = ", param$minpts))

    #ST-DBSCAN uses projected coordinates
    stdb <- stdbscan(x=data_x$Long_proj, y=data_x$Lat_proj,
                     time=data_x$cum_time, eps=param$eps, eps2=param$eps2, minpts=para
m$minpts)

    #Append cluster field to participant data
    stdb <- as.data.frame(cbind(data_x,stdb_cluster=stdb$cluster))
    stdb$transit = (stdb$stdb_cluster == 0)

    #Output csv of results
    print(sprintf("writing csv of clustered data (STDBSCAN): %s", file_path))
    write.csv(stdb, file_path, row.names = FALSE)


    #Let's visualize where the clusters are.
```

```
    qplot(stdb$Long_proj, stdb$Lat_proj, colour=stdb$stdb_cluster, shape = stdb$transi
t)


    colors <- c("#999999", "#E69F00")

    colors <- colors[as.numeric(stdb$transit)]

    #Choosing the number of visually distinct colors that equals to the number of ST-D
BSCAN clusters

    colors <- distinctColorPalette(k=max(stdb$stdb_cluster))

    #3 Dimensional scatter plot of latitude, longitude, date

    plot3d(stdb$Long_proj, stdb$Date, stdb$Lat_proj, col=colors[as.factor(stdb$stdb_cl
uster)], box=F,

           xlab='Longitude',

           ylab='Date', zlab='Latitude')

}

##

##

##  Importing Participant Data: ./Participant 1002/Participant 1002 Imputed.csv

##

##  Projecting coordinates[1] "Running ST-DBSCAN with the following parameters: Eps =
200 , Eps2 = 20 , minpts =  10"

## [1] "writing csv of clustered data (STDBSCAN): T:\\Participant 1002\\Participant 10
02 Imputed STDBSCAN 200 20 10.csv"
```

The last few lines of the code chunk above produces a figure such as the one below, which shows ST-DBSCAN results. It is a 3-dimensional plot of latitude, longitude and time, and each color represents a different cluster (with one of the colors representing cluster 0 – i.e., transit points).

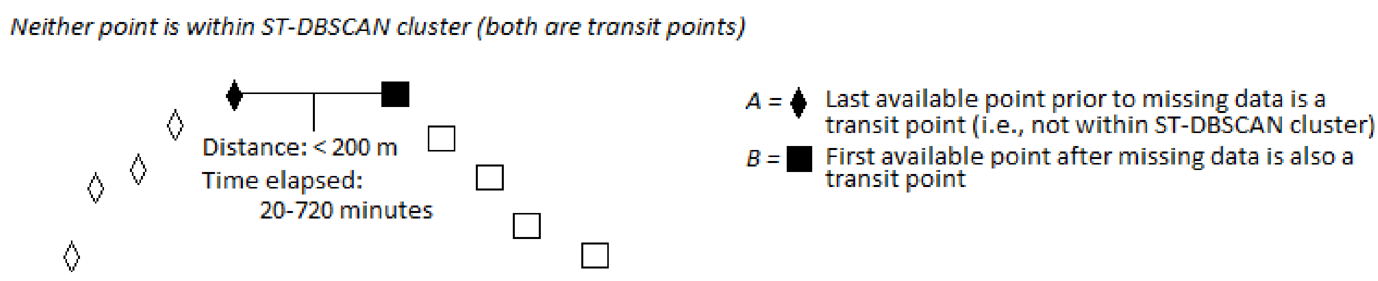

Latitude
Date
Longitude

ADDITIONAL DATA CLEANING, DBSCAN AND TIME VARIABLES

First, we do some data cleaning make sure that the clusters given by ST-DBSCAN are non-overlapping. For instance, if consecutive points correspond to clusters 3, 3, 3, 4, 4, 3, 3, 3, 4, 4, 3, the clusters need to be separated out, and the code below addresses these issues. (Note that eventually the clusters may be merged.)

Secondly, because of missing data, the number of clusters identified through ST-DBSCAN is generally an underestimate of the total number of destinations that an individual visited during the study period. As an attempt to correct for this bias, an algorithm was developed to supplement ST-DBSCAN and enable for the identification of additional clusters and modify existing ones in the presence of missing data. This missing data algorithm focuses on four distinct scenarios.

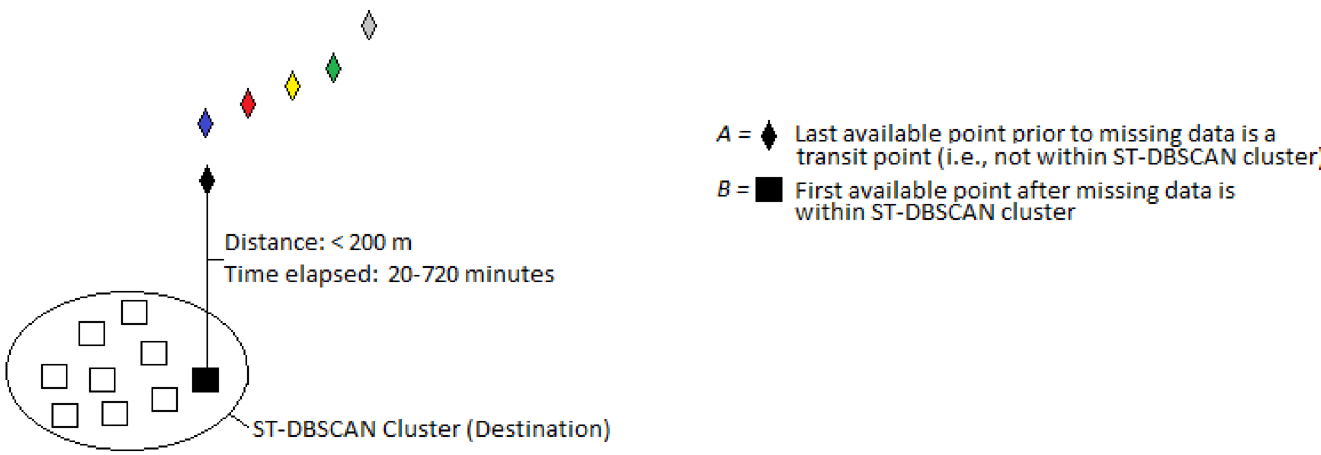
In the first scenario, there are two consecutive transit points, called A and B, whose distance from one another is less than eps1 distance units (200 m), but is more than eps2 time units (20 min) apart. Although these points are not placed within a cluster by STDBSCAN due to the value of the eps2 parameter (and possibly the minpts parameter), the supplementary algorithm puts these two points into a cluster if they are less than 12 hours (720 minutes) apart. This is because it is likely that participants went inside a building directly after point A, lost satellite reception, and were inside the building (i.e., at a destination) until reappearing at point B. Twelve hours as the maximum time was selected because larger values might increase the likelihood that an individual left the building between points A and B, but either did not carry or charge the phone.



The remaining three scenarios do not identify new clusters, but either merge existing clusters with transit points, or merge two existing clusters into one. This is needed not for the identification of destinations, but for a more accurate calculation of the temporal variables, such as time spent outside of home or in transit, described below.

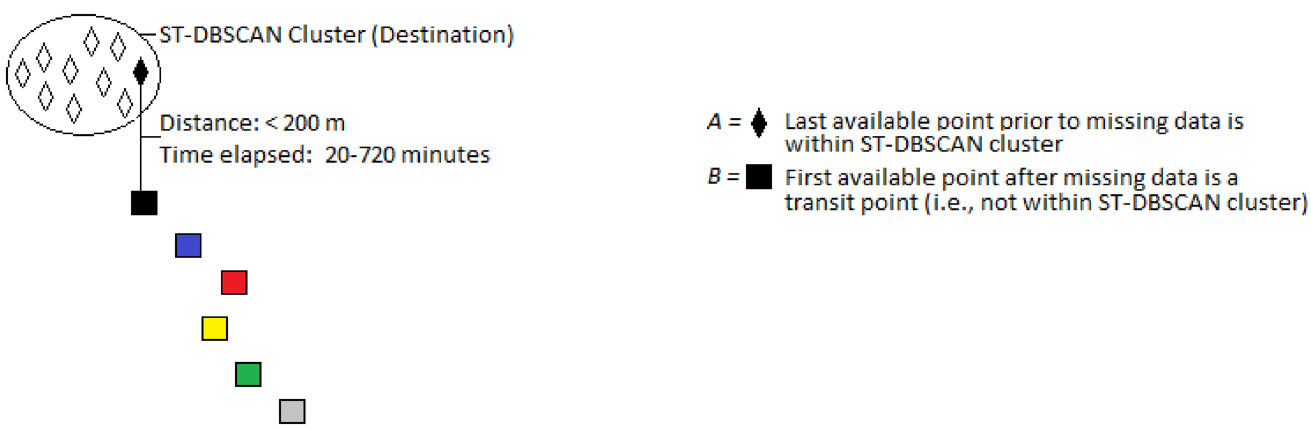
In the second scenario, two consecutive points are identified: A is a transit point and B is part of an ST-DBSCAN destination cluster. As in scenario 1, these points are within a distance of eps1 units, but more than eps2 time units apart. An assumption of this scenario is that the person went inside after point A and did not have good satellite reception until point B. Therefore, if A and B are less than 12 hours apart, transit point A is placed in the cluster which contains B.

1 Point is within ST-DBSCAN cluster, 1 is a transit point.

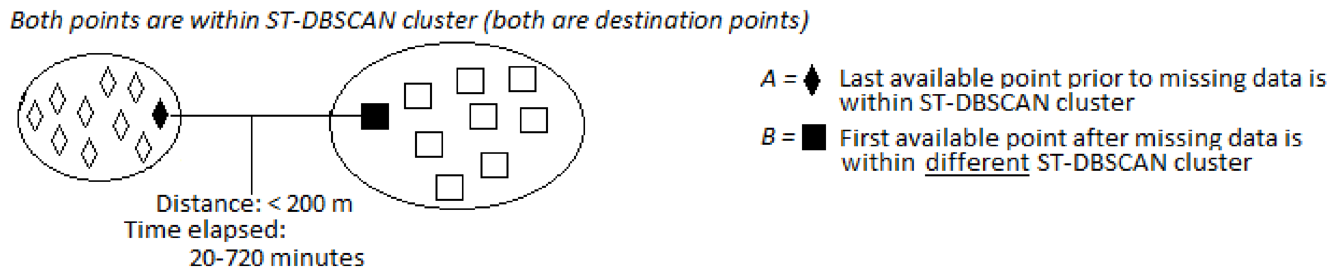


The third scenario is similar to the second, except the roles of points A and B are reversed: A is part of an ST-DBSCAN cluster and B is a transit point. If A and B are less than 12 hours apart, transit point B is placed in the cluster which contains A.

1 Point is within ST-DBSCAN cluster, 1 is a transit point.



In the fourth scenario, two consecutive points A and B are within a distance of eps1, but fall within two separate ST-DBSCAN clusters (1 and 2) because they are more than eps2 time units apart. If points A and B are within 12 hours of one another and the centroids of clusters 1 and 2 are within eps1 (200 m), the algorithm combines the clusters 1 and 2 into a single cluster.



After that, we identify all ST-DBSCAN clusters which correspond to home locations. These are defined as ST-DBSCAN clusters whose centroids are within 200 meters of the geocoded home address. All other destinations are considered to be non-home destinations, and all locations that have the ST-DBSCAN cluster 0 are transit points. Based on that, we can easily calculate the following variables:

1. Time at home destinations

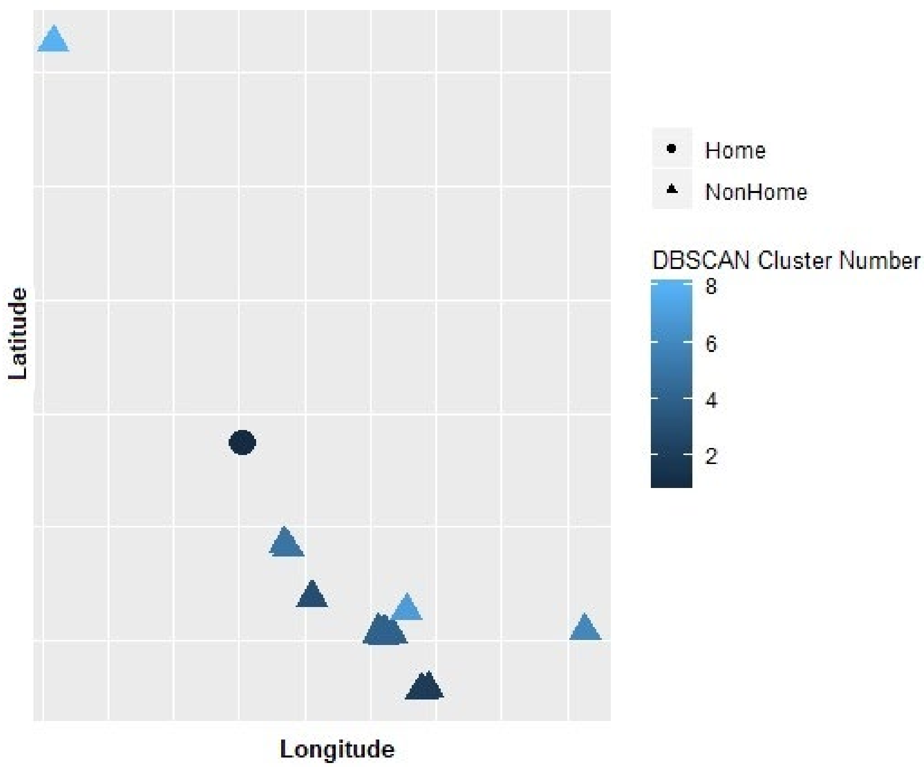
2. Time at non-home destinations

3. Time in transit

4. Missing time, defined as the total of 20160 minutes - (Time at home + Time at other destinations + Time in transit)

Then, we calculate the number of unique destinations for each individual. Individuals may come to some destinations more than once over the course of the study. Such destinations might include their home, work, or treatment providers. To identify unique destinations, we run the DBSCAN clusering algorithm on centroids of ST-DBSCAN clusters. This algorithm uses two parameters, eps (which is the distance between points, which we set to 200 meters as in ST-DBSCAN), and MinPts, which is the minimum number of points needed to form a cluster (which we set to two). Unique destinations are then calculated as the sum of 1) the number of DBSCAN clusters and 2) the number of destinations in cluster 0 (i.e., destinations which only appeared once over the course of the study).

Here's a plot of the DBSCAN clusters



In addition, we also identify which of the post-processed clusters are home clusters. A home cluster is a cluster whose centroid is within 200 meters of the geocoded home address. We also calculate:

- Time spent at home (we compute the difference between the start and end times for each home cluster and sum across all home clusters)

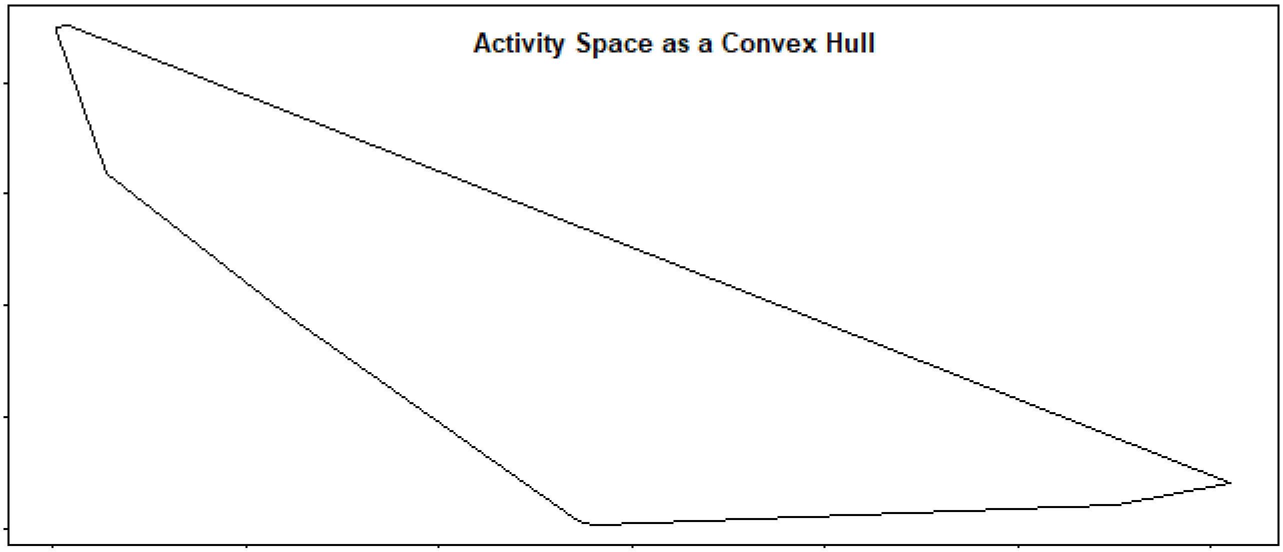
- Time spent at non-home destinations (we compute the difference between the start and end times for each non-home cluster and sum across all non-home clusters)

- Time in transit (we compute the number of rows in the data where cluster = 0)

- Non-missing time (calculated as the sum of Time at Home, Time at Other Destinations, and Time in Transit)

- Missing time (calculated as 20160 minutes/14 day period - Non-missing Time)

- Activity Space Area (computed as the convex hull around the points). Below is a plot of a sample activity space.



- Distance Traveled (calculated as the distance between all consecutive points that aren't within the same destination)

- Number of non-missing days (days with 720+ minutes, or 50%+ of data)

- Median Daily Activity Space Area (for non-missing days)

```
#Set Working Directory

setwd("T:\\")


library(Jmisc)

library(dplyr)

library(fuzzyjoin)


#Make list of paths to data files

data_path_list3 <- list_data_paths("Participant [[:digit:]]{4} Imputed STDBSCAN [[:dig
it:]]{3} [[:digit:]]{2,4} [[:digit:]]{1,2}.csv",TRUE)


#Directory for exporting dbscan csv

out_dir <- "T:\\Data"


data_x <- read.csv(data_path_list3[1], stringsAsFactors = FALSE, colClasses = c("Date"
= "POSIXct"))


#Scenarios 1-4

for (path3 in data_path_list3[2]){

   participant_number <- substr(path3,15,18)
```

```
   dir_name <- dirname(path3)

   cat("\n\n", "PARTICIPANT",participant_number)


   #Import data

   data_x <- read.csv(path3, stringsAsFactors = FALSE, colClasses = c("Date" = "POSIXc
t"))


   #Record number of unique stdb_clusters before postprocessing

   clust_pre <- sort(unique(data_x$stdb_cluster))

   num_clust_pre <- length(clust_pre)




   ######################################

   #####  PRELIMINARY DATA CLEANING #####

   ######################################


   #Sometimes ST-DBSCAN places transit points between points that are within a cluster
. We will make all these transit

   #points be part of the cluster.


   #If a cluster is completely within another non-transit cluster, we need to split up
the cluster that it is within into

   #two clusters

   data_x$cluster <- data_x$stdb_cluster


   #If:

   #1) The point is not in transit cluster, and

   #2) The previous point IS NOT in the same cluster, and

   #3) Some of the earlier points (10+ observations ago) ARE in the same cluster as th
e original point, then:

   #Create new cluster that equals to the original cluster*1000000

   for (i in seq(21,nrow(data_x))){

      if  (data_x$cluster[i]!=0 &

          #data_x$cluster[i-1]!=0 &

           data_x$cluster[i]!=data_x$cluster[i-1] &

          (#data_x$cluster[i]==data_x$cluster[i-2] |

           #data_x$cluster[i]==data_x$cluster[i-3] |

           #data_x$cluster[i]==data_x$cluster[i-4] |
```

```
           #data_x$cluster[i]==data_x$cluster[i-5] |
           #data_x$cluster[i]==data_x$cluster[i-6] |
           #data_x$cluster[i]==data_x$cluster[i-7] |
           #data_x$cluster[i]==data_x$cluster[i-8] |
           #data_x$cluster[i]==data_x$cluster[i-9] |
           data_x$cluster[i]==data_x$cluster[i-10] |
           data_x$cluster[i]==data_x$cluster[i-11] |
           data_x$cluster[i]==data_x$cluster[i-12] |
           data_x$cluster[i]==data_x$cluster[i-13] |
           data_x$cluster[i]==data_x$cluster[i-14] |
           data_x$cluster[i]==data_x$cluster[i-15] |
           data_x$cluster[i]==data_x$cluster[i-16] |
           data_x$cluster[i]==data_x$cluster[i-17] |
           data_x$cluster[i]==data_x$cluster[i-18] |
           data_x$cluster[i]==data_x$cluster[i-19] |
           data_x$cluster[i]==data_x$cluster[i-20])) {
            data_x$cluster[i]=data_x$cluster[i]*1000000
         }
   }


   #If:
   #1) The cluster ID of the point after operation above is the same as the cluster ID before the operation above, and
   #2) The cluster ID of the point equals the cluster ID of the previous point divided by 1000000 (that is, if previous
   #   point was changed by the operation above), then:
   #Merge the point into the same cluster as the previous point (i.e., assign it the same cluster ID as the previous
   #point)


   #That is, if the point's cluster membership wasn't changed, but the previous point's cluster membership WAS changed,
   #Change the point's cluster membership
   for (i in seq(2, nrow(data_x))){
      if (data_x$cluster[i]==data_x$stdb_cluster[i] &
          data_x$cluster[i]==data_x$cluster[i-1]/1000000){
            data_x$cluster[i]=data_x$cluster[i-1]
          }
```

```
   }


   #Sometimes, after all the cleaning above, there are still some clusters which only
contain 1 point.
   #We will convert these points to 0 (transportation) clusters.
   for (i in seq(2, nrow(data_x)-1)){
      if (data_x$cluster[i]!=0 &
          data_x$cluster[i-1]==0 &
          data_x$cluster[i+1]==0){
            data_x$cluster[i]=0
          }
   }


   #Removing the cluster variable
   data_x$stdb_cluster = data_x$cluster
   data_x$cluster <- NULL


   #Let's look at maximum and minimum time by cluster. If the operations above aren't
done, then the min and max times can    #be confusing.
   cumtime.max <- as.data.frame(aggregate(data_x$cum_time,list(data_x$stdb_cluster),ma
x))
   colnames(cumtime.max) <- c('stdb_cluster','CumTimeMax')
   cumtime.max <- cumtime.max[which(cumtime.max$stdb_cluster!=0),]


   cumtime.min <- as.data.frame(aggregate(data_x$cum_time,list(data_x$stdb_cluster),mi
n))
   colnames(cumtime.min) <- c('stdb_cluster','CumTimeMin')
   cumtime.min <- cumtime.min[which(cumtime.min$stdb_cluster!=0),]


   cumtime <- cbind(cumtime.min, cumtime.max)[,-3]


   #If time stamp of a point is between minimum and maximum time of a cluster, then we
want to assign that point to that
   #cluster.
   data_x_cumtime <- fuzzy_left_join(data_x,cumtime, by=c("cum_time"="CumTimeMin", "cu
m_time"="CumTimeMax"),
                                     match_fun=list(`>=`,`<=`))


   #Replace NA cluster ID in stdb_cluster.y with 0
```

```
   data_x_cumtime$stdb_cluster.y<-replace(data_x_cumtime$stdb_cluster.y, is.na(data_x_
cumtime$stdb_cluster.y), 0)

   data_x_cumtime$stdb_cluster <- data_x_cumtime$stdb_cluster.y


   #Removing unnecessary variables

   data_x_cumtime[, c('stdb_cluster.y', 'stdb_cluster.x', 'CumTimeMin', 'CumTimeMax')]
<- list(NULL)


   data_x <- data_x_cumtime


   #Defining transit variable as those where cluster = 0

   data_x$transit = (data_x$stdb_cluster == 0)



   ######################################

   #####         SCENARIO 1         #####

   ######################################

   cluster_list <- c()


   for (i in seq(2,nrow(data_x))){

    if(between(data_x$time_gap[i],20,720)                     # if 20 < time_gap < 720
mins

       & data_x$distance[i] < 200                             # and distance < 200

       & data_x$stdb_cluster[i]==0                            # and current stdb_clust
er = 0

       & data_x$stdb_cluster[i-1]==0                          # and prev stdb_cluster
= 0

      # & is.na(data_x$ID[i])==FALSE                          # and current obs is not
imputed

      # & is.na(data_x$ID[i-1])==FALSE)                       # and prev obs is not im
puted

   ){

      stdb_cluster_id <- max(data_x$stdb_cluster)+1           # create new stdb_cluste
r number

      data_x$stdb_cluster[i] <- stdb_cluster_id               # assign new stdb_cluste
r number to current obs

      data_x$stdb_cluster[i-1] <- stdb_cluster_id             # assign new stdb_cluste
r number to prev obs

      cluster_list<- c(cluster_list,stdb_cluster_id)

    }

   }
```

```
   cat("\n\n", "Scenario 1: Number of stdb_clusters created:", length(cluster_list))
   cat("\n\n", "ID(s) of stdb_clusters created:", cluster_list)



   #####################################
   #####         SCENARIO 2        #####
   #####################################
   df <- data_x
   df$NextClus <- lead(df$stdb_cluster)
   df$NextDist <- lead(df$distance)
   df$NextGap <- lead(df$time_gap)

   clustered_obs <- 0
   for (i in seq(1,nrow(df)-1)){
     if(between(df$NextGap[i],0,720)                   # if 20 < time_gap < 720 mins
           & df$NextDist[i] < 200                      # and distance < 200
           & df$stdb_cluster[i]==0                     # and current stdb_cluster = 0
           & df$NextClus[i]!=0){                       # and next stdb_cluster != 0
       stdb_cluster_id2 <- df$NextClus[i]
       df$stdb_cluster[i] <- stdb_cluster_id2          # add current obs to stdb_clust
er of next obs
       cat("\n\n","Scenario 2: Adding observation ID" ,df$ID[i]," to stdb_cluster",std
b_cluster_id2)
       clustered_obs <- clustered_obs + 1
       }
   }
   if (clustered_obs == 0){
     cat("\n\n", "Scenario 2: stdb_clusters unchanged")
   }
   data_x <- df



   #####################################
   #####         SCENARIO 3        #####
   #####################################
   df <- data_x
   df$LagClus <- lag(df$stdb_cluster)
```

```
   df$LagGap <- lag(df$time_gap)


   clustered_obs <- 0

   for (i in seq(2,nrow(df))){

     if(between(df$time_gap[i],0,720)                  # if 20 < time_gap < 720 mins

            & df$distance[i] < 200                     # and distance < 200

            & df$stdb_cluster[i]==0                    # and current stdb_cluster = 0

            & df$LagClus[i]!=0){                       # and prev stdb_cluster != 0

       stdb_cluster_id3 <- df$LagClus[i]

       df$stdb_cluster[i] <- stdb_cluster_id3          # add current obs to stdb_clust
er of prev obs

       cat("\n\n","Scenario 3: Adding observation ID ",df$ID[i]," to stdb_cluster",std
b_cluster_id3)

       clustered_obs <- clustered_obs + 1

       }

   }

   if (clustered_obs == 0){

     cat("\n\n", "Scenario 3: stdb_clusters unchanged")

   }

   data_x <- df



   ######################################

   #####         SCENARIO 4         #####

   ######################################

   #(Code for Scenario 4 in the functions.r file is incorrect, but it is correct here)

   df <- data_x


   #Calculate centroids of each ST-DBSCAN cluster

   centroids <- as.data.frame(aggregate(data_x[,8:9],list(data_x$stdb_cluster),mean))

   colnames(centroids) <- c('stdb_cluster','CentroidLongProj','CentroidLatProj')


   #Calculate the minimum date in each ST-DBSCAN cluster

   centroids_date <- as.data.frame(aggregate(data_x[,1],list(data_x$stdb_cluster), min
))

   colnames(centroids_date) <- c('stdb_cluster','CentroidMinDate')


   #Merge the minimum date and centroids into a single data set
```

```
   centroids_fin <- cbind(centroids, centroids_date)

   centroids_fin <- centroids_fin[,-4]        #Removing the second stdb_cluster variab
le


   #Removing observations from cluster 0

   centroids_fin <- centroids_fin[which(centroids_fin$stdb_cluster != 0),]


   #Sorting by time

   centroids_fin1 <- centroids_fin[order(centroids_fin$CentroidMinDate),]


   #Creating centroids of next cluster

   centroids_fin1$NextCentroidLatProj = lead(centroids_fin1$CentroidLatProj)

   centroids_fin1$NextCentroidLongProj = lead(centroids_fin1$CentroidLongProj)


   #Calculating distance between current cluster centroids and next cluster centroids

   centroids_fin1$DistToNextNon0Cluster <- sqrt((centroids_fin1$CentroidLongProj-centr
oids_fin1$NextCentroidLongProj)**2+

                                      (centroids_fin1$CentroidLatProj-centroids_fin1$N
extCentroidLatProj)**2)


   #Before merging, create a new data frame with the 0 row

   centroids_fin1[nrow(centroids_fin1)+1,] <- NA

   #Replace NA cluster ID with 0

   centroids_fin1$stdb_cluster<-replace(centroids_fin1$stdb_cluster, is.na(centroids_f
in1$stdb_cluster), 0)

   #Replace NA distance with 1000000

   centroids_fin1$DistToNextNon0Cluster<-replace(centroids_fin1$DistToNextNon0Cluster,

                                              is.na(centroids_fin1$DistToNextNon0Clust
er), 1000000)


   #Let's merge this centroid data frame with the original point level data frame, by
cluster ID, and then sort by time

   data_x_merge <- merge(data_x, centroids_fin1, by="stdb_cluster")

   data_x_merge1 <- data_x_merge[order(data_x_merge$Date),]


   data_x_merge1$stdb_cluster_id4 <- data_x_merge1$stdb_cluster


   #Let's do the cluster merging

   for (i in seq(1,nrow(data_x_merge1)-1)){
```

```
       if (data_x_merge1$stdb_cluster[i] != 0                             #If current
cluster is a non-transit cluster

            & data_x_merge1$NextClus[i] != 0                              #Next cluste
r is a non-transit cluster

            & data_x_merge1$stdb_cluster[i] != data_x_merge1$NextClus[i]  #Current clu
ster is not equal to next cluster

            & data_x_merge1$DistToNextNon0Cluster[i] < 200

            & data_x_merge1$time_gap[i+1] <= 720) {             #Distance between clus
ters is < 200m

                            data_x_merge1$stdb_cluster_id4[i] = data_x_merge1$NextClus
[i]

            }

   }


   #Now, we are going to take the maximum value of each new cluster (stdb_cluster_id4)
within each old cluster

   scenario4 <- as.data.frame(aggregate(data_x_merge1$stdb_cluster_id4,list(data_x_mer
ge1$stdb_cluster),max))

   #scenario4$x<-replace(scenario4$x, 3, 3)

   #scenario4$x<-replace(scenario4$x, 2, 2)

   #Here, each old cluster is called stdb_cluster and each new cluster is called x

   colnames(scenario4) <- c('stdb_cluster','x')

   #Let's duplicate variable x and call it stdb_cluster_id4fin

   scenario4$stdb_cluster_id4fin <- scenario4$x


   #For each observation, if stdb_cluster equals to x in the previous observation, var
iable stdb_cluster_id4fin should

   #take on its own value from the previous observation. Doing it this way enables the
merging of more than two

   #consecutive clusters.

   for (i in seq(2,nrow(scenario4))){

       if (scenario4$stdb_cluster[i]==scenario4$x[i-1])

            {             #Distance between clusters is < 200m

                            scenario4$stdb_cluster_id4fin[i] = scenario4$stdb_cluster_
id4fin[i-1]

            }

   }


   scenario4 <- scenario4[,-2]        #Removing variable x
```

```
   #Merging with point-level data which will now have variable stdb_cluster_id4fin (cl
uster ID after scenario 4)

   data_x_merge2 <- merge(data_x_merge1, scenario4, by="stdb_cluster")

   data_x <- data_x_merge2[order(data_x_merge2$Date),]  #Sorting by date


   #Subtracting 1 because of transportation cluster

   cat("\n\n","Scenario 4: Number of clusters before merging of consecutive clusters:"
,

       length(unique(data_x$stdb_cluster))-1)

   cat("\n\n","Scenario 4: Final number of clusters after merging of consecutive clust
ers: ",

       length(unique(data_x$stdb_cluster_id4fin))-1)

   cat("\n\n","Scenario 4: Number of clusters merged: ",

       length(unique(data_x$stdb_cluster))-length(unique(data_x$stdb_cluster_id4fin)))


   #Updating transit and stdb_cluster variables

   data_x$transit = (data_x$stdb_cluster == 0)

   data_x$stdb_cluster <- data_x$stdb_cluster_id4fin

   df <- data_x



   #Printing Messages

   # Final number of unique stdb_clusters after scenarios 1-4

   clust_post <- sort(unique(data_x$stdb_cluster))

   num_clust_post <- length(clust_post)-1


   #Updating the NextClus and LagClus variables

   data_x$NextClus = lead(data_x$stdb_cluster)

   data_x$LagClus = lag(data_x$stdb_cluster)


   ##################################

   ##### IDENTIFYING HOME LOCATIONS #####

   ##################################


   #We are dealing with the participant whose ID equals to the Participant Number. (Th
at is, we are selecting the

   #appropriate ID number)

   Home <- subset(Projected_Home[which (HomeAll$ID == as.numeric(as.character(particip
ant_number))),])
```

```
   #Participant's Home location

   colnames(Home) <- c('ID','Long','Lat')

   Home1 <- data.matrix(Home[,2:3])


   #Calculate distance between projected home location and projected ST-DBSCAN cluster
centroids

   #Averaging Lat_Proj and Long_Proj by cluster

   centroids <- as.data.frame(aggregate(data_x[,9:10],list(data_x$stdb_cluster),mean))

   colnames(centroids) <-c('stdb_cluster', 'Long_proj', 'Lat_proj')

   centroids$Home_Lat = rep(Home1[2], nrow(centroids))

   centroids$Home_Long = rep(Home1[1], nrow(centroids))


   #Identify each ST-DBSCAN cluster as a home or non-home cluster based on whether its
centroid is within 200 m of

   #geocoded home location

   centroids$dist <- sqrt(((centroids$Lat_proj-centroids$Home_Lat)**2)+((centroids$Lon
g_proj-centroids$Home_Long)**2))


   #Lat/Long Centroid less than or equal to 200 meters from home, should be a home loc
ation.

   #If it's cluster 0, it's the transit cluster, so we're not interested in it (hence
> 0)

   HomeClusters <- as.data.frame(centroids[which(centroids$dist < 200 & centroids$stdb
_cluster > 0),])

   HomeClusters$Cluster <- rep("Home", nrow(HomeClusters))

   cat("\n\n", "Participant",participant_number,"had", nrow(HomeClusters), "home clust
ers.")


   NonHomeClusters <- as.data.frame(centroids[which(centroids$dist > 200 & centroids$s
tdb_cluster > 0),])

   NonHomeClusters$Cluster <- rep("NonHome", nrow(NonHomeClusters))

   cat("\n\n", "Participant",participant_number,"had", nrow(NonHomeClusters), "non-hom
e clusters.")



   #######################################

   #####  COMPUTING TIME VARIABLES  #####

   #######################################


   #Prepping the data for DBSCAN Analyses below.
```

```
   DBSCANHome <- rbind(HomeClusters,NonHomeClusters)

   #DBSCANHome <- DBSCANHome[c(-1)]

   #DBSCANHome <- DBSCANHome[which(DBSCANHome$stdb_cluster>0),]


   #Calculate Time Spent at Each Cluster

   #Takes the first element of each non-transit cluster

   data_x_start <- data_x[!duplicated(data_x$stdb_cluster) & data_x$stdb_cluster > 0,]


   #Takes the first element of each reversed non-transit cluster (i.e., the last eleme
nt of each cluster)

   data_x_end <- data_x[rev(!duplicated(rev(data_x$stdb_cluster))) & data_x$stdb_clust
er > 0,]


   #Prepping data to have start and end times in a single data frame

   data_x_start$start_time <- data_x_start$cum_time

   data_x_end$end_time <- data_x_end$cum_time


   start_end <- as.data.frame(data_x_start[c(1,25)])   #stdb_cluster and start_time

   start_end$end_time = data_x_end$end_time


   #Total Time variable is the amount of time spent in each cluster (end time - start
time + 1 minute)

   start_end$TotalTime <- (start_end$end_time - start_end$start_time) + 1

   DBSCANHomeTimes<- full_join(start_end,DBSCANHome, by = "stdb_cluster")


   #We want to calculate the total time spent at home and out of home.

   #The aggregate command creates the table that looks like this:

   #Group.1    x

   #Home      [Total Time At Home]

   #NonHome   [Total Time At Non-Home Destinations]


   #So here:

   #[1,2] indicates that we're looking at time at home, which is in the 1st row, 2nd c
olumn, and

   #[2,2] indicates that we're looking at time at non-home destinations, which is in t
he 2nd row, 2nd column.


   #Time at Home
```

```
   SumHome<- aggregate(DBSCANHomeTimes$TotalTime, by=list(DBSCANHomeTimes$Cluster),sum
)[1,2]

   cat("\n\n", "Participant",participant_number,"spent", SumHome, "minutes at home des
tinations.")


   #Time at Non-Home

   SumNonHome<- aggregate(DBSCANHomeTimes$TotalTime, by=list(DBSCANHomeTimes$Cluster),
sum)[2,2]

   cat("\n\n", "Participant",participant_number,"spent", SumNonHome, "minutes at non-h
ome destinations.")


   #Time in Transit is simply calculated as the number of rows in the data_x data fram
e where STDBSCAN Cluster = 0.

   TransitTime <- as.data.frame(subset(data_x, stdb_cluster == 0))

   cat("\n\n", "Participant",participant_number,"spent", nrow(TransitTime), "minutes i
n transit.")


   #Putting all the Time variables into a single data frame

   TimeX <- data.frame(matrix(ncol = 7, nrow = 0))

   TimeX <- as.data.frame(rbind(c("ID" = participant_number,"HomeMins" = SumHome,"NonH
omeMins" =

                                    SumNonHome,"TransitMins" = nrow(TransitTime),"Perc
entHome"=

                                    round(SumHome/sum(SumHome,SumNonHome,nrow(TransitT
ime)),4),"PercentNonHome"=

                                    round(SumNonHome/sum(SumHome,SumNonHome,nrow(Trans
itTime)),4),"PercentTransit"=

                                    round(nrow(TransitTime)/sum(SumHome,SumNonHome,nro
w(TransitTime)),4))))

   TimeSheet <- rbind(TimeX, TimeSheet)

   TimeSheet <- distinct(TimeSheet, ID, .keep_all=TRUE)

   colnames(TimeSheet) <- c("ID","HomeMins","NonHomeMins","TransitMins","PercentHome",
"PercentNonHome","PercentTransit")



   ######################################

   #####           DBSCAN           #####

   ######################################


   #Now it's time to use DBSCAN to compute the number of unique Destinations.

   cat("\n\n", "Running DBSCAN...")
```

```
   #Computing a Euclidean distance matrix (in meters) between all the ST-DBSCAN cluste
r centroids

   dist_xy <- as.matrix(dist(DBSCANHomeTimes[,5:6], method="euclidean",diag=T))


   #Running DBSCAN with parameters eps = 200 and MinPts = 2

   db <- fpc::dbscan(dist_xy, eps = 200, MinPts = 2, scale=FALSE, method="dist")


   #Add dbscan clusters to a new data frame called dbscan_x

   dbscan_x <- cbind(DBSCANHomeTimes, db$cluster)


   #Calculate the number of times each cluster appears (this is really only needed for
clusters labeled as 0)

   dbscan_x$num <- ave(dbscan_x$stdb_cluster, dbscan_x$`db$cluster`, FUN=seq_along)


   #Number of Unique Clusters is the # of clusters 1..n + the number of 0 clusters (wh
ich are also unique destinations)

   #Sometimes there are no 0 clusters, in which case, R yields -Inf as the response, a
nd the number of unique destinations    #is not calculated.

   test <- max(dbscan_x$num[dbscan_x$`db$cluster`==0])

   test1 <- ifelse(is.infinite(test),0,test)

   NumUniqueDest <- sum(max(dbscan_x$`db$cluster`, na.rm=TRUE), test1, na.rm=TRUE)

   cat("\n\n", "Number of unique destinations: ", NumUniqueDest)


   #Each cluster given its final DBSCAN cluster number. Cluster 1 is the home cluster.

   dbscan_x$findbscanclust <- dbscan_x$`db$cluster`   #Taking it from the cluster elem
ent in the db list


   #If cluster = 0, then cluster ID will be # of 0 clusters + the time (1st, 2nd, 3rd,
etc.) it appears in the data

   dbscan_x$findbscanclust[dbscan_x$`db$cluster`==0] <- dbscan_x$num[dbscan_x$`db$clus
ter`==0] +

        max(dbscan_x$`db$cluster`)



   ######################################

   #####    DISTANCE TRAVELED &     #####

   #####    ACTIVITY SPACE AREA     #####

   ######################################
```

```
   #We also calculate the total distance traveled (in km.) over the course of the stud
y, as well as activity space area

   #in sq. km.) The activity space area is calculated using the convex hull command in
R.


   #First, we calculate the total Distance Traveled (in km). Here, we are only calcula
ting the distances between points

   #which aren't in the same cluster.

   dist_traveled <- data_x[which(data_x$stdb_cluster == 0 | data_x$NextClus != data_x$
stdb_cluster),]


   #This is like the dist2_km variable in our ArcGIS/SAS files

   total_distance_km = sum(dist_traveled$NextDist, na.rm=TRUE)/1000

   cat("\n\n", "Total distance (in km) that participant traveled:",total_distance_km)


   #Now, let's calculate the activity space area.

   # create dataframe of timestamp, unprojected xy, and projected xy

   datax_proj <- as.data.frame(cbind(Date = as.Date(as.numeric(as.POSIXct(data_x$Date)
),origin="1990-01-01"), Long =

                                       data_x$Long,Lat = data_x$Lat,Long_Proj = data_x
$Long_proj,Lat_Proj =

                                       data_x$Lat_proj))


   #out_path1 <- paste("S:/RRTC/RRTC 2013-2018/GPS Study - Field Initiated/Data/AccuTr
acking

   #Data/ArcMap/Proj",participant_number,".csv",sep="")

   #write.csv(datax_proj, file_path)


   # create a list containing the indices of coordinates that make the convex hull

   chull_indx <- chull(datax_proj[,4:5])

   # append the first index to the end of the list (to create a closed loop)

   chull_indx <- c(chull_indx, chull_indx[1])

   # extract the coordinates of the convex hull from the matrix of xy coords

   chull_pts <- datax_proj[chull_indx,4:5]


   # plot convex hull as polygon and print area

   #plot(chull_pts, type="n")

   #chull_poly <- polygon(chull_pts)

   chull_area <- polyarea(chull_pts[,2]/1000,chull_pts[,1]/1000) #converting meters to
km#
```

```
   cat("\n\n", "The activity space area is", chull_area, "sq. km.")



   ######################################
   #####        MISSING DAYS        #####
   ######################################

   #A day is considered missing if more than 50% of the data (i.e., more than    #720
minutes) are missing.
   #MissingDays
   #86400 = # seconds in a day

   #Cluster Lag
   data_x$stdb_cluster_lag <- lag(data_x$stdb_cluster)
   #Replacing the NA in the first observation with 0
   data_x$stdb_cluster_lag<-replace(data_x$stdb_cluster_lag, is.na(data_x$stdb_cluster
_lag), 0)

   #Cluster Lead
   data_x$stdb_cluster_lead <- lead(data_x$stdb_cluster)
   #Replacing the NA in the last observation with 0
   data_x$stdb_cluster_lead<-replace(data_x$stdb_cluster_lead, is.na(data_x$stdb_clust
er_lead), 0)

   #Cluster Min and Max Dates
   #Let's expand our data frame to include all missing minutes
   data_x$timestamp<-as.POSIXct(data_x$Date ,format="%m/%d/%y %H:%M:%S")
   #[-1,] removes the zero cluster

   MinTimeByCluster <- aggregate(data_x$cum_time, by=list(data_x$stdb_cluster),min)[-1
,]
   MaxTimeByCluster <- aggregate(data_x$cum_time, by=list(data_x$stdb_cluster),max)[-1
,]
   #[-,3] removes the 3rd column which is the repetition of the cluster ID
   MinMaxTimeByCluster <- cbind(MinTimeByCluster, MaxTimeByCluster)[,-3]
   colnames(MinMaxTimeByCluster) <- c("stdb_cluster", "MinTimeByCluster", "MaxTimeByCl
uster")

   #Let's expand the data frame to include every possible value of cum_time
```

```
   df <- data.frame(seq(data_x$cum_time[1], data_x$cum_time[nrow(data_x)]))

   colnames(df) <- "cum_time"

   fin<-dplyr::full_join(df,data_x,by=c("cum_time"="cum_time"))

   data_x <- fin


   #If cum_time in data_x is between min and max time, merge between (use fuzzy join)
by cum_time

   df <- fuzzy_left_join(data_x,MinMaxTimeByCluster, by=c("cum_time"="MinTimeByCluster
", "cum_time"="MaxTimeByCluster"),                                      match_fun=lis
t(`>=`,`<=`))


   df$stdb_cluster <-df$stdb_cluster.x

   df$stdb_cluster.x <- NULL

   df$stdb_cluster.y <- NULL


   #Replacing NA stdb_cluster with some negative value so that it's not missing

   df$stdb_cluster<-replace(df$stdb_cluster, is.na(df$stdb_cluster), -5)


   #Test is a variable that takes on a value of 1 if Min & Max cumulative time are mis
sing and the observation isn't in

   #a transit cluster

   df$test <- ifelse(df$stdb_cluster == 0, 0, ifelse(is.na(df$MinTimeByCluster) & is.n
a(df$MaxTimeByCluster),1,0))


   nrow_df = nrow(df)


   #Removing all variables where test = 1

   df<-df[!(df$test==1),]

   data_x <- df


   #nonmissing2 <- nrow(data_x)

   #missing2 <- 20160 - nrow(data_x)

   #transit2 <- nrow(data_x) - (SumHome+SumNonHome)


   #Because we did the merging by cum_time, some of the time stamps were missing. We c
an calculate the

   #final time stamp by taking the time stamp of the first observation and adding cum_
time*60 minutes to it.

   data_x$timestamp.final <- data_x$timestamp[1] + (data_x$cum_time*60)

   attributes(data_x$timestamp.final)$tzone<- "America/New_York"
```

```
   data_x$DayOfMonth <- as.numeric(format(as.Date(data_x$timestamp.final,format="%Y-%m
-%d %H:%M:%S",
                                                   tz="America/New_York"), format ="%d"
))*1
   df <- transform(data_x,Day=as.numeric(factor(DayOfMonth)))
   data_x <- df

   ######################################
   #####      BY DAY VARIABLES      #####
   ######################################

   #create a subset grouped by day for each participant
   MissingDays <- data.frame(matrix(ncol = 1, nrow = 0))
   ParticipantMissing<- data.frame(matrix(ncol = 1, nrow = 1))
   MedianActSpace <- data.frame(matrix(ncol = 1, nrow = 1))
   Days <- unique(data_x$Day)
   MinsPerDay <-data.frame(matrix(ncol=1, nrow=1))

   #We create the median of activity space areas for non-missing days. That is, for ea
ch calendar day that is not
   #missing, we calculate the activity space area, and then calculate the median of th
ose areas.

   #Daily Variables
   DayAreas <- matrix(ncol = 1, nrow = 0)
   for (i in Days){
     Day <- data_x[data_x$Day == i,]
     DayX <- max(Day$cum_time, na.rm=TRUE) - min(Day$cum_time, na.rm=TRUE) + 1
     MinsPerDay <- rbind(MinsPerDay,DayX)

     #If we have fewer than 720 minutes, it's a missing day!
     if (DayX < 720) {
        Miss = 1
        chull_area1 <- NA              #Area is missing
     }
     else {
        Miss = 0
        # create a list containing the indices of coordinates that make the convex hul
l
```

```
        Day1 <- Day[!is.na(Day$Long_proj),]
        chull_indx <- chull(Day1[,8:9])
        # append the first index to the end of the list (to create a closed loop)
        chull_indx <- c(chull_indx, chull_indx[1])
        # extract the coordinates of the convex hull from the matrix of xy coords
        chull_Day <- Day1[chull_indx,8:9]
        chull_area1 <- polyarea(chull_Day[,2]/1000,chull_Day[,1]/1000) #converting met
ers to km#
     }

     #Creating the relevant variables
     DayAreas <- rbind(DayAreas,chull_area1)
     MedianActSpace <- median(DayAreas, na.rm=TRUE)
     MissingDays <- rbind(MissingDays,Miss)
   }

   MinsPerDay.df <- as.data.frame(MinsPerDay[-1,])

   cat("\n\n", "The median daily activity space area is", MedianActSpace, "sq. km.")
   cat("\n\n", "The number of missing days is", (14-length(Days))+sum(MissingDays$X0))
   cat("\n\n", "The number of non-missing days is", nrow(MissingDays) - sum(MissingDay
s$X0))


   ######################################
   #####     OTHER CALCULATIONS     #####
   ######################################

   NonMissingMins <- sum(SumHome, SumNonHome, nrow(TransitTime))*1
   #NonMissingPts <- nrow(data_x)
   #DiffMinsPts <- NonMissingMins - NonMissingPts
   MissingMins <- 20160 - NonMissingMins
   MinsOutsideHome <- SumNonHome + nrow(TransitTime)
   NumDestinations <- nrow(DBSCANHomeTimes)*1
   NumNonHomeDest <- nrow(NonHomeClusters)*1

   cat("\n\n", "Participant",participant_number,"had", NonMissingMins, "non-missing mi
nutes.")
```

```
   cat("\n\n", "Participant",participant_number,"had", MissingMins, "missing minutes."
)



   #Putting everything in a single data frame
   OtherX <- data.frame(matrix(ncol = 18, nrow = 0))
   OtherX <- as.data.frame(rbind( c("ID" = participant_number, "NonMissingMinutes" = N
onMissingMins,
                                    "MissingMinutes" = MissingMins, "HomeDestMinutes"
= SumHome,
                                    "NonHomeDestMinutes" = SumNonHome, "TransitMinutes
" = nrow(TransitTime),
                                    "OutsideOfHomeMinutes" = MinsOutsideHome,
                                    "TotalMinutes" = sum(MissingMins, SumHome, SumNonH
ome, nrow(TransitTime)),
                                    "NonMissingPts" = nrow(data_x[!is.na(data_x$Long_p
roj),]),
                                    "TotalDestinations" = NumDestinations, "HomeDestin
ations" = nrow(HomeClusters),
                                    "NonHomeDestinations" = nrow(NonHomeClusters), "Un
iqueDestinations" = NumUniqueDest,
                                    "DistanceTraveledKm" = total_distance_km, "Activit
ySpaceAreaSqKm" = chull_area,
                                    "TotalDays" = length(Days), "NonMissingDays" = nro
w(MissingDays) -
                                      sum(MissingDays$X0), "MissingDays" = (14-length(
Days))+sum(MissingDays$X0),
                                    "MedianDailyActSpace" = MedianActSpace)))


   #These two commands are needed when we're running the loop for multiple participant
s
   OtherSheet <- rbind(OtherX, OtherSheet)
   OtherSheet <- distinct(OtherSheet, ID,.keep_all=TRUE)


   colnames(OtherSheet) <- c("ID","NonMissingMinutes", "MissingMinutes", "HomeDestMinu
tes",
                             "NonHomeDestMinutes", "TransitMinutes", "OutsideOfHomeMin
utes",
                             "TotalMinutes", "NonMissingPts", "TotalDestinations", "Ho
meDestinations",
                             "NonHomeDestinations", "UniqueDestinations","DistanceTrav
eledKm",
                             "ActivitySpaceAreaSqKm", "TotalDays", "NonMissingDays", "
MissingDays",
```

```
                               "MedianDailyActSpace")
}
##
##
##  PARTICIPANT 1002
##
##  Scenario 1: Number of stdb_clusters created: 4
##
##  ID(s) of stdb_clusters created: 68000001 68000002 68000003 68000004
##
##  Scenario 2: Adding observation ID 319  to stdb_cluster 2
##
##  Scenario 2: Adding observation ID 345  to stdb_cluster 3
##
##  Scenario 2: Adding observation ID NA  to stdb_cluster 10
##
##  Scenario 2: Adding observation ID 484  to stdb_cluster 11
##
##  Scenario 2: Adding observation ID 3087  to stdb_cluster 13
##
##  Scenario 2: Adding observation ID 3140  to stdb_cluster 16
##
##  Scenario 2: Adding observation ID 3174  to stdb_cluster 17
##
##  Scenario 2: Adding observation ID 3202  to stdb_cluster 18
##
##  Scenario 2: Adding observation ID NA  to stdb_cluster 23
##
##  Scenario 2: Adding observation ID 3703  to stdb_cluster 25
##
##  Scenario 2: Adding observation ID 4211  to stdb_cluster 28
##
##  Scenario 2: Adding observation ID 4263  to stdb_cluster 29
##
##  Scenario 2: Adding observation ID NA  to stdb_cluster 39
##
##  Scenario 2: Adding observation ID 5644  to stdb_cluster 42
```

```
##
##  Scenario 2: Adding observation ID NA  to stdb_cluster 43
##
##  Scenario 2: Adding observation ID NA  to stdb_cluster 45
##
##  Scenario 2: Adding observation ID 5768  to stdb_cluster 47
##
##  Scenario 2: Adding observation ID 5776  to stdb_cluster 48
##
##  Scenario 2: Adding observation ID 5797  to stdb_cluster 49
##
##  Scenario 2: Adding observation ID 6651  to stdb_cluster 50
##
##  Scenario 2: Adding observation ID NA  to stdb_cluster 51
##
##  Scenario 2: Adding observation ID 6693  to stdb_cluster 52
##
##  Scenario 2: Adding observation ID 8348  to stdb_cluster 56
##
##  Scenario 2: Adding observation ID 8401  to stdb_cluster 58
##
##  Scenario 2: Adding observation ID 8414  to stdb_cluster 59
##
##  Scenario 2: Adding observation ID NA  to stdb_cluster 60
##
##  Scenario 2: Adding observation ID 8970  to stdb_cluster 66
##
##  Scenario 2: Adding observation ID 8994  to stdb_cluster 68
##
##  Scenario 2: Adding observation ID 9176  to stdb_cluster 75
##
##  Scenario 2: Adding observation ID 9729  to stdb_cluster 78
##
##  Scenario 2: Adding observation ID 9765  to stdb_cluster 79
##
##  Scenario 2: Adding observation ID 10408  to stdb_cluster 84
##
```

```
##  Scenario 2: Adding observation ID 10524  to stdb_cluster 88
##
##  Scenario 2: Adding observation ID 10590  to stdb_cluster 89
##
##  Scenario 3: Adding observation ID  312  to stdb_cluster 1
##
##  Scenario 3: Adding observation ID  394  to stdb_cluster 6
##
##  Scenario 3: Adding observation ID  NA  to stdb_cluster 13
##
##  Scenario 3: Adding observation ID  3573  to stdb_cluster 19
##
##  Scenario 3: Adding observation ID  3696  to stdb_cluster 24
##
##  Scenario 3: Adding observation ID  4205  to stdb_cluster 27
##
##  Scenario 3: Adding observation ID  4291  to stdb_cluster 29
##
##  Scenario 3: Adding observation ID  4401  to stdb_cluster 32
##
##  Scenario 3: Adding observation ID  5632  to stdb_cluster 41
##
##  Scenario 3: Adding observation ID  NA  to stdb_cluster 42
##
##  Scenario 3: Adding observation ID  5775  to stdb_cluster 47
##
##  Scenario 3: Adding observation ID  8408  to stdb_cluster 58
##
##  Scenario 3: Adding observation ID  NA  to stdb_cluster 65
##
##  Scenario 3: Adding observation ID  9723  to stdb_cluster 77
##
##  Scenario 3: Adding observation ID  NA  to stdb_cluster 79
##
##  Scenario 3: Adding observation ID  9866  to stdb_cluster 80
##
##  Scenario 3: Adding observation ID  NA  to stdb_cluster 68000004
```

```
##
##  Scenario 3: Adding observation ID  10413  to stdb_cluster 84
##
##  Scenario 3: Adding observation ID  10485  to stdb_cluster 86
##
##  Scenario 4: Number of clusters before merging of consecutive clusters: 95
##
##  Scenario 4: Final number of clusters after merging of consecutive clusters:  75
##
##  Scenario 4: Number of clusters merged:  20
##
##  Participant 1002 had 12 home clusters.
##
##  Participant 1002 had 63 non-home clusters.
##
##  Participant 1002 spent 13967 minutes at home destinations.
##
##  Participant 1002 spent 3977 minutes at non-home destinations.
##
##  Participant 1002 spent 936 minutes in transit.
##
##  Running DBSCAN...
##
##  Number of unique destinations:  26
##
##  Total distance (in km) that participant traveled: 430.6735
##
##  The activity space area is 109.7901 sq. km.
##
##  The median daily activity space area is 17.8718 sq. km.
##
##  The number of missing days is 0
##
##  The number of non-missing days is 14
##
##  Participant 1002 had 18880 non-missing minutes.
##
```

```
##  Participant 1002 had 1280 missing minutes.
write.csv(OtherSheet,file="T:\\Data\\ParticipantDataMeasuresTEST.csv")
```