Processing data sources for analysis

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- Start by importing libraries

```
library(tidyverse)
library(lubridate)
library(ggplot2)
library(readr)
```

- Read the csv files of the Divvy data into separate dataframes
- Combine all dataframes into a single dataframe

```
setwd("/home/mikiR/remote_transfer/")
X202110_divvy_tripdata <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/202110-divvy-tripdata.csv")
X202111_divvy_tripdata <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/202111-divvy-tripdata.csv")
X202112_divvy_tripdata <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/202112-divvy-tripdata.csv")
X202201_divvy_tripdata <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/202201-divvy-tripdata.csv")
X202202_divvy_tripdata <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/202202-divvy-tripdata.csv")
X202203_divvy_tripdata <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/202203-divvy-tripdata.csv")
X202204_divvy_tripdata <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/202204-divvy-tripdata.csv")
X202205_divvy_tripdata <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/202205-divvy-tripdata.csv")
X202206_divvy_tripdata <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/202206-divvy-tripdata.csv")
X202207_divvy_tripdata <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/202207-divvy-tripdata.csv")
X202208_divvy_tripdata <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/202208-divvy-tripdata.csv")
X202209_divvy_tripdata <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/202209-divvy-tripdata.csv")
X202210_divvy_tripdata <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/202210-divvy-tripdata.csv")

all_trips <- bind_rows(
              X202110_divvy_tripdata, X202111_divvy_tripdata, X202112_divvy_tripdata, X202201_divvy_tripdata,
              X202202_divvy_tripdata, X202203_divvy_tripdata, X202204_divvy_tripdata, X202205_divvy_tripdata,
              X202206_divvy_tripdata, X202207_divvy_tripdata, X202208_divvy_tripdata, X202209_divvy_tripdata,
              X202210_divvy_tripdata)
```

- Create new columns from date field, split into
  - month
  - day
  - year
  - day of week
  - time of day
  - hour

```
all_trips$date <- as.Date(all_trips$started_at)
all_trips$month <- format(as.Date(all_trips$date), "%m")
all_trips$day <- format(as.Date(all_trips$date), "%d")
all_trips$year <- format(as.Date(all_trips$date), "%Y")
all_trips$day_of_week <- format(as.Date(all_trips$date), "%A")
all_trips$timeofday <- format(as.POSIXct(all_trips$started_at), format = "%H:%M:%S")
all_trips$hours <- format(as.POSIXct(all_trips$started_at), format = "%H")
```

- Create column ridelength calculated from the difference of ended_at and started_at
- Convert column value into numeric

```
all_trips$ride_length <- difftime(all_trips$ended_at,all_trips$started_at)
all_trips$ride_length <- as.numeric(as.character(all_trips$ride_length))
```

- Remove bad data

```
all_trips_v2 <- all_trips[!(all_trips$ride_length<0),]
```

- Move bad data into a dataframe to doublecheck

```
all_trips_errors <- all_trips[(all_trips$ride_length<0),]
```

- Read the climate data into a dataframe

```
setwd("/home/mikiR/remote_transfer/")
climate_chicago_202110_202210 <-
  read_csv("./20221205-capstone_datascience-01/002_data/001_csv/climate_chicago_202110-202210.csv")
```

- Convert the date field in the climate data frame to date format

```
climate_chicago_202110_202210$date <- as.Date(climate_chicago_202110_202210$date)
```

- Trying to calculate the distance between gps coordinates start_lng & start_lat / end_lng & end_lat
- Import geosphere library

```
library(geosphere)
```

- Calculate the distance between the start and end coordinates using the Haversine formula
- Create new column geodist with the calculated distance

```
all_trips_v3 <- all_trips_v2 %>%
        mutate(geodist = distHaversine(
            cbind(all_trips_v2$start_lng,all_trips_v2$start_lat),
            cbind(all_trips_v2$end_lng,all_trips_v2$end_lat)))
```

- Filter all trips with distance = 0 into a dataframe called round_trips, the assumtion being that when the trip ends where it started

```
round_trips = filter(all_trips_v3,geodist == 0)
```

- While working with the data, I noticed some very long rental periods (> 86400 seconds, aka one day) I think this would be maintenance work, as this would be unlikely to be a rental from a customer
- Also, I filtered out all rentals under 1 minute, since these do not represent useful customer behavior as well
- Similarly, all entries that have a geodist value of NA - because they don't have a return station value, are similarly out for maintenance, or stolen, or in case of very short rental periods of a few seconds, maybe a booking error or system test
- I filtered these sets into dataframes into short_ride long_ride and nadist_ride in order to analyze a little bit

```
short_ride <- (filter(all_trips_v3,ride_length < 60 & !is.na(geodist)))
long_ride <- (filter(all_trips_v3,ride_length > 86400 & !is.na(geodist)))
nadist_ride <- (filter(all_trips_v3,is.na(geodist)))

summary(filter(long_ride)$ride_length)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   86445   89809   97212  222552  207746 2442301
```

```
summary(filter(nadist_ride)$ride_length)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       6   89990   89994  175632   90001 2483235
```

- Create a new dataframe all_trips_v4 containing only trips under 86400 s & geodist not NA

```
all_trips_v4 <- (filter(all_trips_v3,ride_length < 86400 & ride_length > 60 & ride_length != 0 & !is.na(geodist)))
summary(filter(all_trips_v4)$ride_length)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    61.0   366.0   634.0   998.6  1129.0 86391.0
```

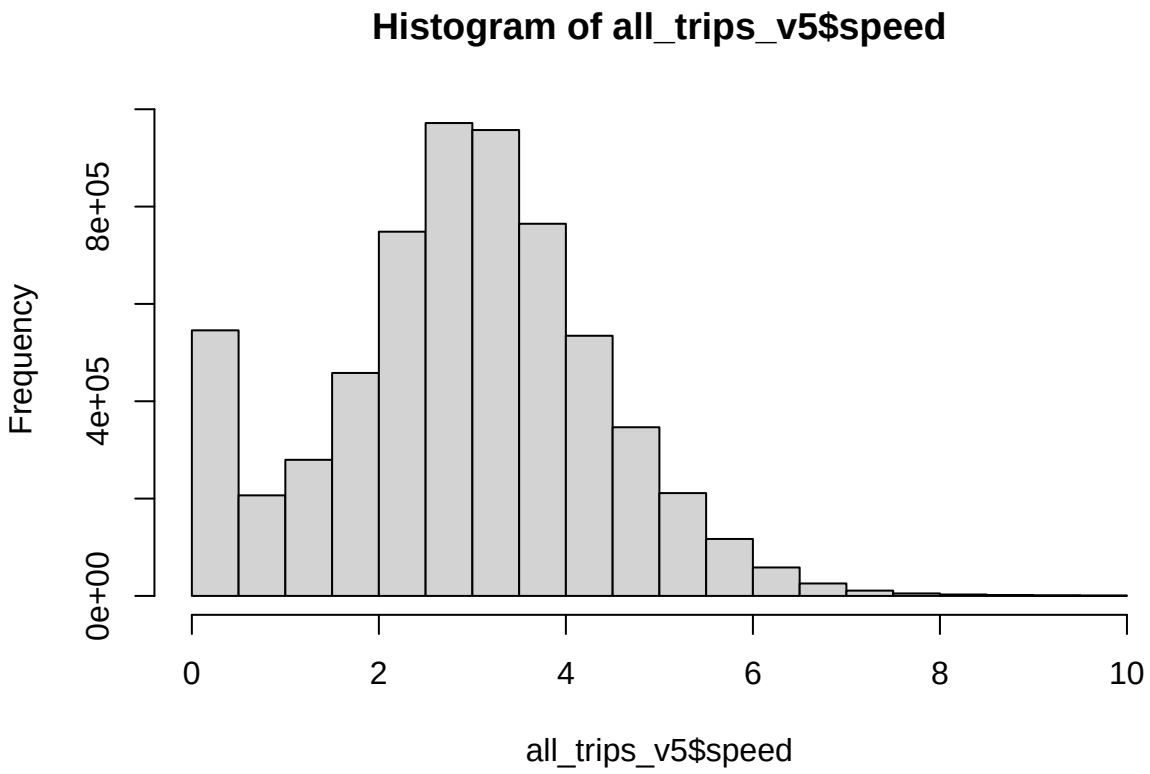
- Another oddity I found in the data was rides with very high speeds, when dividing geodist in meters by ridelength in seconds
- I created a new column speed with the calculated value geodist / ride_length, and filter out all rides with speed above 10 m/s (36 km/h or 22.4 mph) - pedal assisted bikes are capped at 20 mph
- If the value is very low, this can mean a leisurely ride, or a ride that ends close to where it began, whereas a high value can only mean transport by other means, and since rented bikes are not allowed on CTA (https://www.transitchicago.com/bikeandride/) this can only mean the bike was not being used by a customer

- looking at the distribution of values, the bulk of non round trips seems to be around the average biking speed, the mean of the speed column being at 2.9 m/s - 6.5 mph

```
all_trips_v5 <- all_trips_v4 %>%
  mutate(speed = geodist / ride_length) %>%
  filter(speed < 10)
summary(all_trips_v5$speed)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.059   2.957   2.897   3.822  10.000
```

```
hist(all_trips_v5$speed)
```



- I decided to create a new dataframe, all_trips_v5, filtering out the entries with impausibly high speed