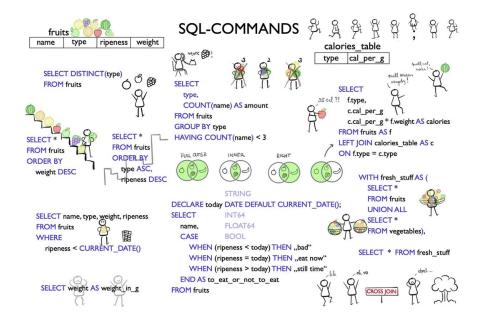
- 1. Create a Google Cloud Account
- 2. Download R Studio
- 3. Upload dataset to Google Cloud Storage (create bucket)
- 4. Access dataset in Big Query (upload from GCS due to file size)
- 5. Some Helper basic SQL commands:



Source: https://medium.com/data-school/the-best-bigquery-sql-cheat-sheet-for-beginners-81c762f72845

- 6. Data explained -> note for next trimester to keep note which units were being used
- Timestamp date + time (inc seconds) + time zone
- Timestamp_AEST date + time (inc seconds) in current AEST time (Melbourne time is AEST in summer and AEDT in winter)
- Date AEST date only in format dd/mm/yyyy
- Distance expressed in kilometers
- Enhanced_altitude we ride faster at altitude than at sea level
- Ascent- usually expressed in %
- Grade Gradient, Slope. It is steepness of an ascent of descent. Usually expressed in %
- Calories burnt
- Enhanced_speed km/ min?
- Heart rate in beats per minute
- Temperature
- Cadence RPM number of revolutions per minute (pedalling rate). An RPM = 60 means 1 pedal revolution (whole 360 degrees) a second
- Power- measures how much work a cyclist is doing on the bike, and is expressed in watts

200-300 is average for recreational cycling

- GPS_accuracy
- Session_ID add a unique one for each session
- User_ID unique for each user
- Age
- Gender
- Weight in kg
- FTP (functional threshold power)

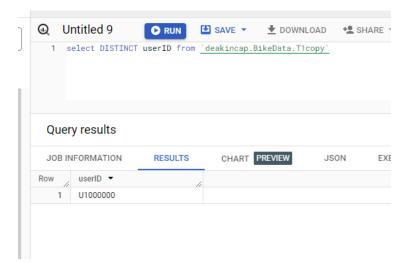
Add:

- Duration = distance / speed; check units

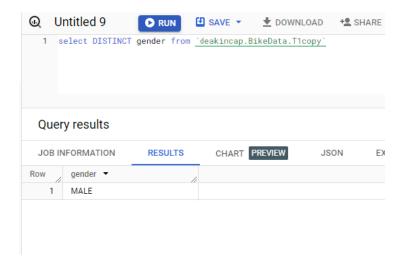
Plan:

- Copy dataset , work on copy
- Check data types and units
- Make note that there are null values throughout the dataset
- Insert uniquely generated sessionID's
- Insert 'duration' column & create a formula to calculate it − need to check the data units ✔
- DATA WRANGLING

Consistent userID check:



a) Consistent gender check (making sure MALE appears 1 way, not male, MALE, Male, MaLe etc)



b) Unify degrees of precision:

enhanced_speed	enhanced_sp
25.5384	
32.8788	
29.9952	
28.2384	
26.0892	
9.2808	
23.1912	
26.7804	
23.49	
30.096	
32.7888	
29.9268	
25.5672	
24.6708	
30.1968	
28.6128	
30.9996	
30.3696	
32.9292	
30.87	

- Finish data Wrangling:
- Delete rows with missing values, nulls
- BigQuery does not have a built-in K-means clustering function, so I will have to perform clustering in Rstudio
- Example patterns:

Time of day patterns, intensity levels, activity profile (casual, pro, intensive), effort consistency,

week 3 progress report:

- Have connected with the P1 SmartBike project
- Have agreed with Victor (Web Dev) on creating an additional page featuring visualizations and taking advantage
 of findings from clustering, such as fitness levels, engagement patterns, training intensity, goal achievement (+
 projected results) and more
- Started Data Wrangling process in BigQuery so that the structure and quality of data can yield reliable results of data clustering will be finished with Wrangling tonight; Will also try to use SQL queries in BigQuery to perform trend analysis.
- BigQuery does not have a built-in K-means clustering function, so I will have to perform clustering in Rstudio start tomorrow
- Will list all the possible inferences that can be drawn from the analysis in R, and contact Web Dev Blke team regarding which they would be most interested in featuring on the additional page
- By tues/ wed myself and Victor will start working on the visualization and I will additionally import the clustered data to Tableau to showcase different visualizations there (dashboards)
- Ask Ella about data Warehouse report (BikeData T1)
- NEXT trimester: application that fetches clustering results from your R script via an API.
- 1. Stream Data into BigQuery (use API)
- 2. Cluster in Rstudio
- 3. Visualization with React (?)
- Integrate app with R script
- Integrate React with API
- 4. Schedule Real time updates

Saturday 25 Nov 2023

So the data was collected as data points, which means that every second a data update was recorded and inserted in the CSV file.

1. Adding session ID to those workouts that were conducted consecutively. Any state of 'idle' for over 5 minutes (line 17) would be categorized as a new session. Later development can feature a 'Are you still here?' countdown of 5 minutes, when the bike is not being used (if the rider stopped interacting).

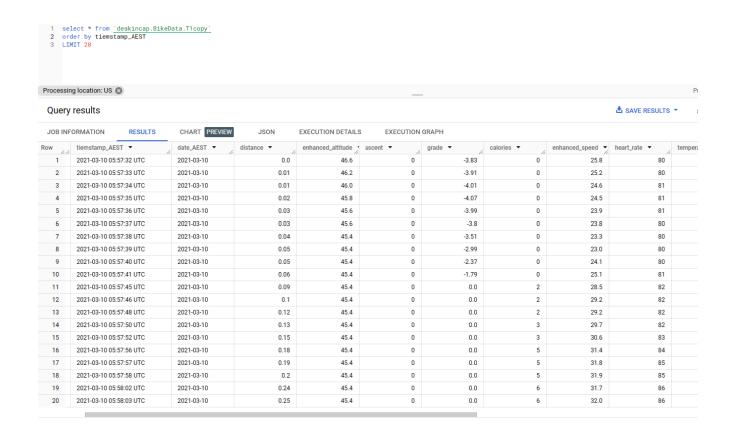
```
2 UPDATE <u>`deakincap.BikeData.T1copy3`</u>
3 SET session_ID = Subquery.session_ID
4 FROM (
5
     WITH WorkoutSessions AS (
6
       SELECT
         tiemstamp_AEST,
8
         heart_rate,
         LAG(tiemstamp_AEST) OVER (ORDER BY tiemstamp_AEST) AS prev_timestamp,
9
10
        TIMESTAMP_DIFF(tiemstamp_AEST, LAG(tiemstamp_AEST) OVER (ORDER BY tiemstamp_AEST), MINUTE) AS time_diff
11
12
         `deakincap.BikeData.T1copy3`
13
14
15
      SELECT
16
       tiemstamp_AEST,
       IFNULL(SUM(IF(time_diff > 5 OR prev_timestamp IS NULL, 1, 0))
17
18
       OVER (ORDER BY tiemstamp_AEST), 0) + 1 AS session_ID
19
     FROM
20
     WorkoutSessions
21 ) AS Subquery
22 WHERE <u>`deakincap.BikeData.Tlcopy3`.tiemstamp_AEST</u> = Subquery.tiemstamp_AEST;
```

Result: (last column)

userID ▼	age ▼	gender ▼	weight ▼	FTP ▼	session_ID ▼
U1000000	33	MALE	80	301	512
U1000000	33	MALE	80	301	512
U1000000	33	MALE	80	301	512
U1000000	33	MALE	80	301	260
U1000000	33	MALE	80	301	260
U1000000	33	MALE	80	301	516
U1000000	33	MALE	80	301	519
U1000000	33	MALE	80	301	519
U1000000	33	MALE	80	301	519
U1000000	33	MALE	80	301	519
U1000000	33	MALE	80	301	522
U1000000	33	MALE	80	301	522
U1000000	33	MALE	80	301	523

In order to prepare data so that each category would reflect within a particular session and / or time window, I
decided to group the records by day, hour and userID.

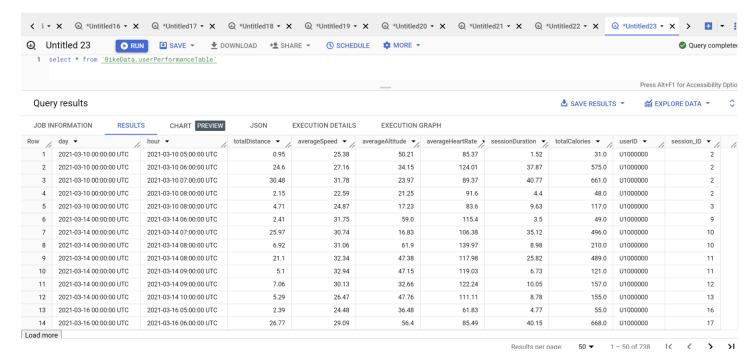
BEFORE:



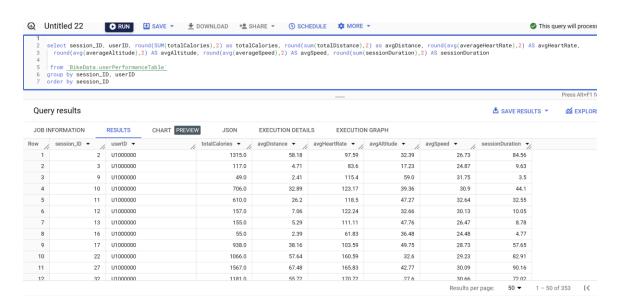
CREATE SORTED DATA TABLE 'userPerformanceTable', making sure no null values appear

```
create table deakincap.BikeData.userPerformanceTable AS
    SELECT
      DATE_TRUNC(tiemstamp_AEST, DAY) AS day,
      DATE_TRUNC(tiemstamp_AEST, HOUR) AS hour,
      round(MAX(distance) - MIN(distance), 2) AS totalDistance,
      round(AVG(enhanced_speed),2) AS averageSpeed,
      round(AVG(enhanced_altitude),2) AS averageAltitude,
 8
      round(AVG(heart_rate),2) AS averageHeartRate,
      round(COUNT(DISTINCT TIMESTAMP_TRUNC(tiemstamp_AEST, second)) / 60, 2) AS sessionDuration,
10
      ROUND(MAX(calories) - MIN(calories), 2) AS totalCalories,
11
      userID,
12
      session_ID
13
14
      `deakincap.BikeData.T1copy3`
15
16
      day, hour, userID, session_ID
17
18
      averageHeartRate IS NOT NULL
19
      AND totalDistance IS NOT NULL
      AND averageSpeed IS NOT NULL
20
21
      AND averageAltitude IS NOT NULL
22
      AND totalCalories IS NOT NULL
23
      AND sessionDuration IS NOT NULL
24
    ORDER BY
25
     day, hour;
```

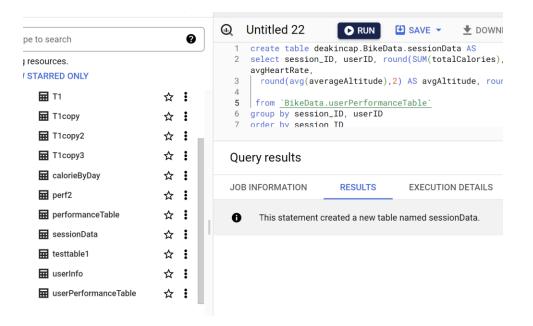
AFTER:



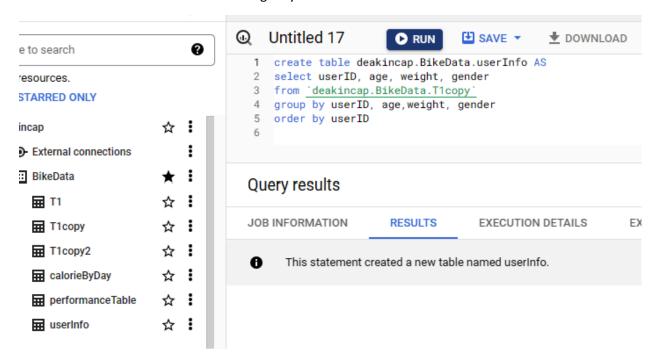
From here we can filter this table by each session's data:



So I will also save that Query result to a new Table called 'sessionData':



3. Create a user data table featuring only user - related data



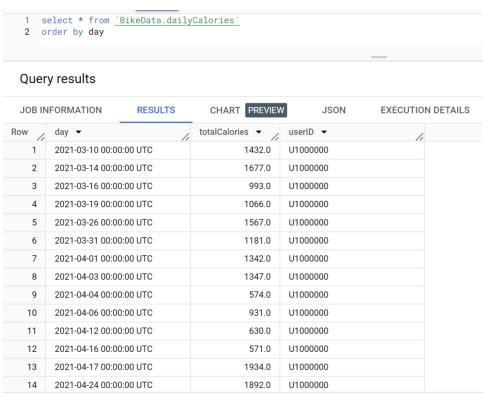


Here we only have 1 user. In the future this table would show all users by userID and their personal data

4. Create a table 'dailyCalories' that would show total calories by day and respective userID it belongs to:

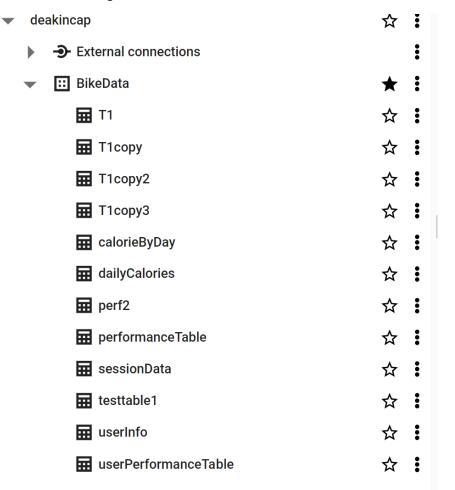
```
1    create table deakincap.BikeData.dailyCalories AS
2    select day,
3    round(sum(totalCalories),2) AS totalCalories,
4    userID
5    from `BikeData.userPerformanceTable`
6    group by day, userID
7    having totalCalories IS NOT NULL
8    order by day
```

RESULT:



Results per pa

5. Now, having those 3 tables: userPerformanceTable, userInfo and dailyCalories



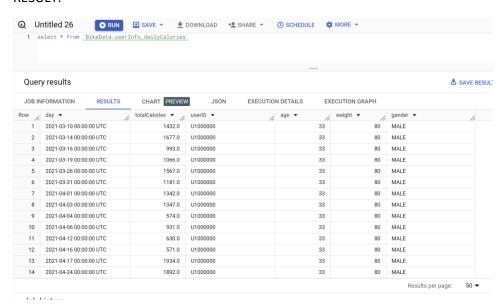
We can perform joins so that we retrieve the data needed for each particular purpose, such as:

a) Calories by day for a relevant user, featuring personal data

dailyCalories + userInfo = userInfo_dailyCalories



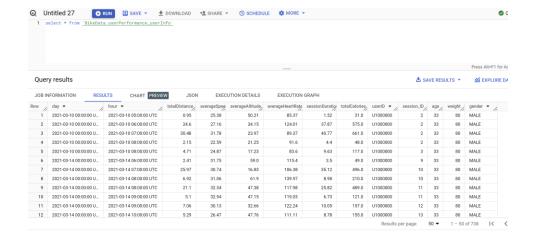
RESULT:



b) Showing performance by day, by the hour for each user, featuring their personal info userPerformance + userInfo = userPerformance userInfo

```
1 create table deakincap.BikeData.userPerformance_userInfo AS
2 select t1.* , t2.age, t2.weight, t2.gender
3 from `BikeData.userPerformanceTable` as t1
4 left outer join
5 `BikeData.userInfo` as t2
6 on t1.userID = t2.userID
7 order by 1
```

RESULT:



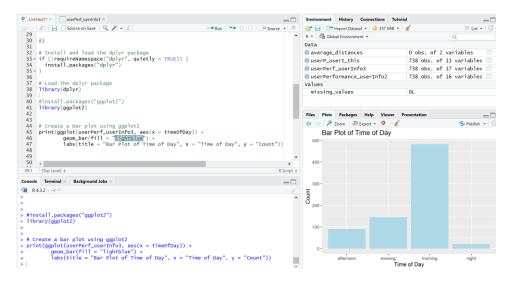
order by 1,2

Additional: add a separate date and time columns as R need to work with those values only, not as a whole timestamp; also add a 'string' column called 'timeOfDay' with 4 acceptable values: 'morning', 'afternoon', 'evening' and 'night'.

```
■ SAVE * ▼ DOWNLOAD
eg Untitica 20
  1 ALTER TABLE deakincap.BikeData.userPerformanceTable
  2 ADD COLUMN IF NOT EXISTS dayDateCol DATE;
 2 UPDATE deakincap.BikeData.userPerformanceTable
    SET dayDateCol = DATE(FORMAT_TIMESTAMP('%Y-%m-%d', day))
 3
 4
    where 1=1;
 5
      2 #1
      3 ALTER TABLE _'deakincap.BikeData.userPerformanceTable'
         ADD COLUMN IF NOT EXISTS timeCol TIME;
      5
      6
      8 UPDATE 'deakincap.BikeData.userPerformanceTable'
      9 SET timeCol = TIME(hour)
     10 where 1=1
   create table <u>'deakincap.BikeData.userPerformance_userinfo2'</u> AS
   select t1.*, t2.age, t2,weight, t2.gender
   from 'BikeData.userPerformanceTable' as t1
  left outer join
   'BikeData.userInfo' as t2
6
   on t1.userID = t2.userID
```

```
2 #1
3 ALTER TABLE deakincap.BikeData.userPerformance_userinfo2
4 ADD COLUMN IF NOT EXISTS timeOfDay STRING;
7 UPDATE deakincap.BikeData.userPerformance_userinfo2
8
   SET timeOfDay =
9
     CASE
10
       WHEN EXTRACT(HOUR FROM hour) BETWEEN 6 AND 11 THEN 'morning'
11
       WHEN EXTRACT(HOUR FROM hour) BETWEEN 12 AND 15 THEN 'afternoon'
12
       WHEN EXTRACT(HOUR FROM hour) BETWEEN 16 AND 21 THEN 'evening'
13
     END
14
15
     where 1=1;
```

Result in R:



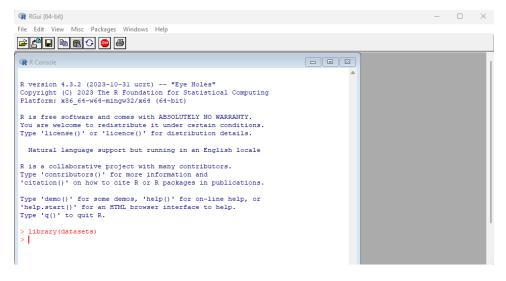
Then export the 'userPerformance_userInfo2' table

6. At this point we can export both joined tables (I exported to Google Sheets, downloaded onto my local computer, changes to .xls format) from point 4, import them to RStudio and start working on Data Clustering.

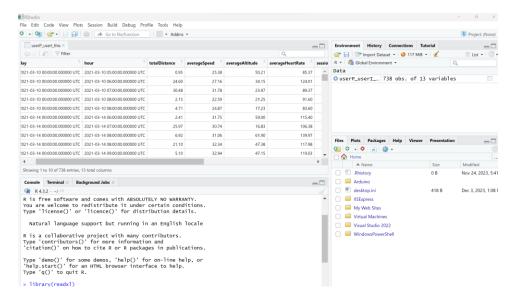
Tuesday (28.11) - onwards

RStudio (K-means cluster analysis)

- 1. In order to import dataset to RStudio it needs to be in .xls format
- 2. Download R:



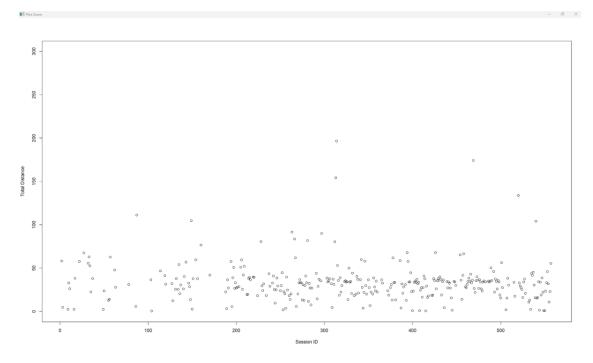
And R studio:



- 3. Correlation analysis
- There is a weak positive correlation between totalDistance and sessionDuration.
- There is a weak negative correlation between totalDistance and averageHeartRate.
- There is a very weak negative correlation between **sessionDuration** and **averageHeartRate**.

```
213
              # correlation analysis
  214
        str(userPerf_userInfo3[, c("totalDistance", "sessionDuration", "averageHeartRate")])
  215
  216
  217
        userPerf_userInfo3$totalDistance <- as.numeric(userPerf_userInfo3$totalDistance)</pre>
  218
219
        user \texttt{Perf\_userInfo3\$sessionDuration} \ <- \ as.numeric (user \texttt{Perf\_userInfo3\$sessionDuration})
        userPerf_userInfo3$averageHeartRate <- as.numeric(userPerf_userInfo3$averageHeartRate)
  221
        cor(userPerf_userInfo3[, c("totalDistance", "sessionDuration", "averageHeartRate")])
  222
  223
  224
        (Top Level) $
Console
       Terminal ×
                      Background Jobs ×
R 4.3.2 · ~/
 $ averageHeartRate: chr [1:738] "85.37" "160.35" "115.0" "103.27"
> userPerf_userInfo3$totalDistance <- as.numeric(userPerf_userInfo3$totalDistance)</pre>
> userPerf_userInfo3$sessionDuration <- as.numeric(userPerf_userInfo3$sessionDuration)
> userPerf_userInfo3$averageHeartRate <- as.numeric(userPerf_userInfo3$averageHeartRate)
> cor(userPerf_userInfo3[, c("totalDistance", "sessionDuration", "averageHeartRate")])
                     totalDistance sessionDuration averageHeartRate 1.0000000 0.18779799 -0.11144762
totalDistance
sessionDuration
                           0.1877980
                                              1.00000000
                                                                   -0.02299837
averageHeartRate
                         -0.1114476
                                             -0.02299837
                                                                    1.00000000
```

4. Time series analysis: session_ID against total distance for that session. The session_ID were assigned in an ascending order to reflect time accurately



We can clearly see that most of the sessions were below 50 km. A session was created as a continuous performance with less than 5 min of idle time.

5. Analysis for particular weekdays

Add weekday in Big Query:

```
ALTER TABLE deakincap.BikeData.userPerformance_userinfo2

ADD COLUMN weekdayName STRING GENERATED ALWAYS AS (FORMAT_DATE('%A', DATE(day))) STORED;
```

Or weekday column in R:

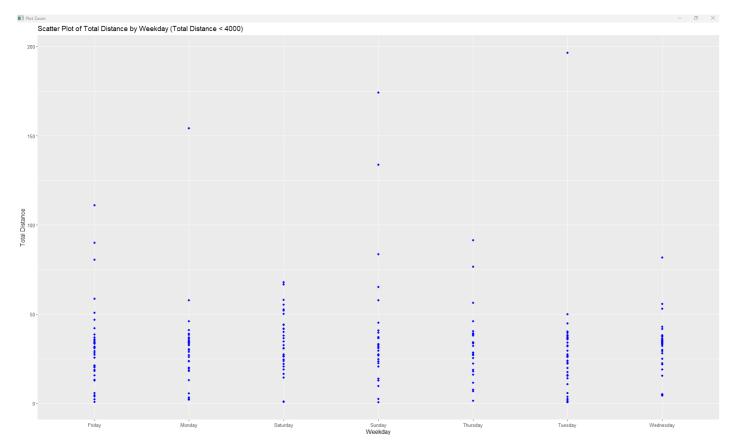
```
# add weekday name
install.packages("lubridate")
library(lubridate)

userPerf_userInfo3$weekday_name <- weekdays(userPerf_userInfo3$day)</pre>
```

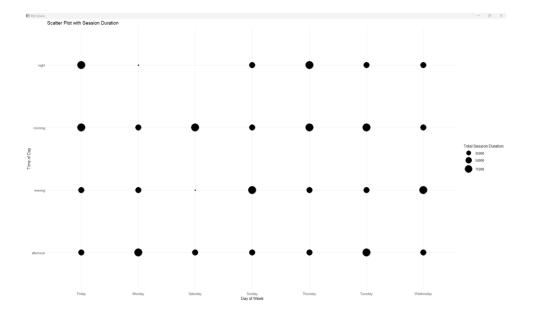


6. Take totalDistance by every session (group by in SQL) and create a scatter plot against each weekday in R. Remove some outliers that slipped out my Data Wrangling in GCS by filtering out totalDistance < 44000:

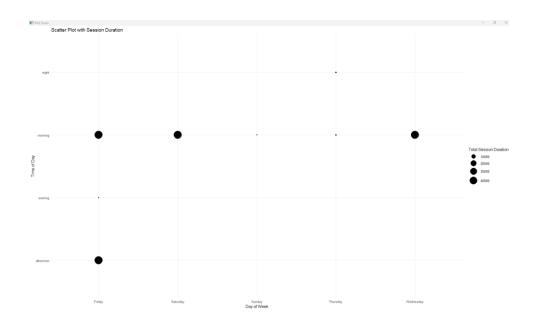
	day	hour \$	totalDistance
97	2022-06-22 00:00:00.000000 UTC	2022-06-22 12:00:00.000000 UTC	44971.00
98	2021-10-22 00:00:00.000000 UTC	2021-10-22 14:00:00.000000 UTC	44970.00
99	2022-01-16 00:00:00.000000 UTC	2022-01-16 17:00:00.000000 UTC	44965.00
100	2021-10-24 00:00:00.000000 UTC	2021-10-24 08:00:00.000000 UTC	44965.00
101	2022-06-22 00:00:00.000000 UTC	2022-06-22 12:00:00.000000 UTC	44963.00
102	2022-01-06 00:00:00.000000 UTC	2022-01-06 19:00:00.000000 UTC	44962.00
103	2021-06-27 00:00:00.000000 UTC	2021-06-27 14:00:00.000000 UTC	44962.00
104	2021-09-08 00:00:00.000000 UTC	2021-09-08 09:00:00.000000 UTC	44961.00
105	2021-04-06 00:00:00.000000 UTC	2021-04-06 05:00:00.000000 UTC	44959.00
106	2022-06-09 00:00:00.000000 UTC	2022-06-09 12:00:00.000000 UTC	44957.00
107	2021-10-24 00:00:00.000000 UTC	2021-10-24 05:00:00.000000 UTC	44955.00
108	2022-11-09 00:00:00.000000 UTC	2022-11-09 17:00:00.000000 UTC	44952.00
109	2022-10-29 00:00:00.000000 UTC	2022-10-29 08:00:00.000000 UTC	44942.00
110	2022-06-04 00:00:00.000000 UTC	2022-06-04 10:00:00.000000 UTC	44935.00
111	2021-05-27 00:00:00.000000 UTC	2021-05-27 18:00:00.000000 UTC	44933.00
112	2022-05-01 00:00:00.000000 UTC	2022-05-01 15:00:00.000000 UTC	44931.00
113	2021-07-10 00:00:00.000000 UTC	2021-07-10 09:00:00.000000 UTC	44930.00
114	2021-10-22 00:00:00.000000 UTC	2021-10-22 13:00:00.000000 UTC	44927.00
115	2021-12-27 00:00:00.000000 UTC	2021-12-27 10:00:00.000000 UTC	120.95
116	2022-07-24 00:00:00.000000 UTC	2022-07-24 09:00:00.000000 UTC	101.61
117	2021-12-28 00:00:00.000000 UTC	2021-12-28 10:00:00.000000 UTC	100.96
118	2021-11-24 00:00:00.000000 UTC	2021-11-24 17:00:00.000000 UTC	66.28
119	2021-05-07 00:00:00.000000 UTC	2021-05-07 16:00:00.000000 UTC	65.11
120	2021-10-28 00:00:00.000000 UTC	2021-10-28 16:00:00.000000 UTC	51.27
121	2021-04-03 00:00:00.000000 UTC	2021-04-03 13:00:00.000000 UTC	36.47
122	2022-11-19 00:00:00.000000 UTC	2022-11-19 07:00:00.000000 UTC	34.16



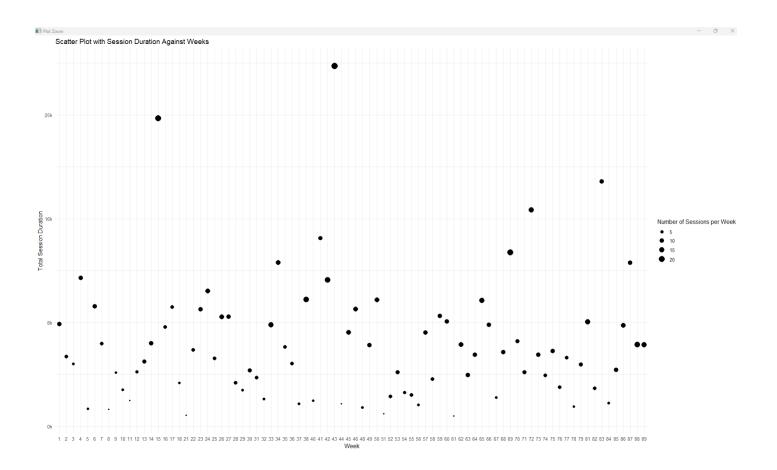
7. Categorize records by day of the week, and time of day. Show sessionDuration as dots and vary their size depending on the length of the session. This one is for the entire dataset. Later could be narrowed down to a particular week, and displayed as a 'weekly summary'



... then see the most recent week:



8. All days grouped into weeks against the total session duration. The size of the dot represents the number of sessions that week



- 9. What is K-Means Clustering?
- One of the most popular unsupervised learning technique
- Used to group together observations

- Using a fixed number of clusters (centroid), group together observations based on similarities
- Uses Euclidean distance
- a) The dataset for clustering Is the `BikeData.userPerformance_userInfo2_new` that will be referenced in github at the end of the document. We take this dataset and group it according to sessions, as we would like insight into each individual session stats.

So in Big Query we will perform the grouping:

```
select sum(totalDistance) AS totalDistance,
 2
      avg(averageSpeed) AS averageSpeed,
      avg(averageAltitude) AS averageAltitude,
 3
      avg(averageHeartRate) AS averageHeartRate,
 4
      sum(sessionDuration) AS sessionDuration,
 5
 6
      sum(totalCalories) AS totalCalories,
 7
      userID,
      session_ID,
 8
      dayDateCol,
 9
      timeCol,
10
      age, weight, gender, timeOfDay, weekdayName
11
12
     from `BikeData.userPerformance_userInfo2_new`
13
      group by session_ID, userID,
14
15
      dayDateCol,
      timeCol,
16
17
      age, weight, gender, timeOfDay, weekdayName
18
      order by session_ID
19
20
```

Save the dataset as .xls and import to R Studio.

b) Apart from data, import the libraries needed. Do some more data checks (I had to filter out some outliers).

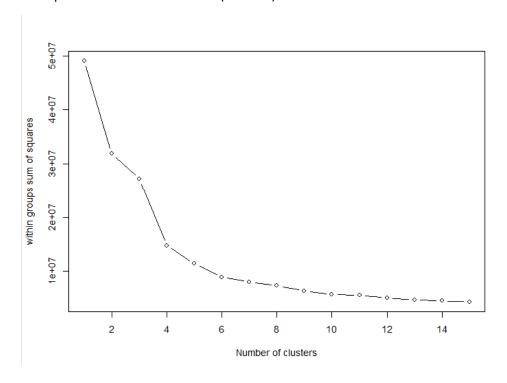
```
Rstudio_script.R* | my_data | newest_joined |
    🔎 📶 📙 🗌 Source on Save 🔍 🎢 🗸
 577 # install : https://cran.rstudio.com/bin/windows/Rtools/rtools43/rtools.html
 578 # then :
 579 install.packages("stats")
 580 install.packages("dplyr")
581 install.packages("ggplot2")
 582 install.packages("ggfortify")
 583
 584 library(stats)
 585
       library(dplyr)
      library(ggplot2)
 586
 587
      library(ggfortify)
 588
 589
     View(newest_joined)
 590
 591 # store all numeric (not char, not string in a separate data object called my_data)
 592
 593
                         # OPTION 1 ----
 594 -
 595
                        # my_data grouped by session_id
 596
 597
                         # define wssplot function, where we grouped dataset by session_ID
 598 -
                         wssplot <- function(data, nc = 15, seed = 1234) {
 599
                           wss <- (nrow(data) - 1) * sum(apply(data[, -1], 2, var))
 600 +
                           for (i in 2:nc) {
                              set.seed(seed)
 601
 602
                              wss[i] <- sum(kmeans(data[, -1], centers = i)$withinss)</pre>
 603 4
                           plot(1:nc, wss, type = "b", xlab = "Number of clusters", ylab = "Within groups sum of squares")
  604
 605 ^
 606
 607
                         # prepare data
 608
                         my_data <- newest_joined %>%
 609
                           select(1, 2, 4, 5, 6, 8) %>%
 610
                           filter(totalDistance < 40000 & sessionDuration < 40000) %>%
 611
                           mutate all(as.numeric)
 612
 613
                         # Group by session_ID and calculate summary statistics
 614
                          grouped_data <- my_data %>%
 615
                           group_by(session_ID) %>%
 616
                           summarise(
 617
                              totDistance = sum(totalDistance),
                              avgSpeed = mean(averageSpeed),
 618
 619
                              avgHeartRate = mean(averageHeartRate),
 620
                              sessDur = sum(sessionDuration),
 621
                              totCalories = sum(totalCalories)
 622
 623
 624
                         # wssplot to choose the optimum number of clusters
 625
                         wssplot(grouped_data)
 626
                         # exclude session_ID for kmeans clustering
 627
 628
                         KM <- kmeans(grouped_data[, -1], 6) # exclude session_ID here as we needed it for grouping only
 629
 630
                         # visualize the results
 631
                          autoplot(KM, data = grouped_data, frame = TRUE)
 632
 633
                          # view the cluster centers
587:19 (Top Level) $
Console Terminal × Background Jobs ×
R 4.3.2 · ~/ ≈
                    # view the cluster centers
                    KM$centers
 totDistance avgSpeed avgHeartRate
                                        sessDur totCalories
                        149.3857 88.022105
                                                 1787.4211
1
    73.01105 29.64618
     18.70049 30.35226
                           155.7045 22.849146
                                                   438.3780
                                                  3901.0000
    162.97000 29.14604
                           155.2922 120.077500
    28.90036 30.01611
                           159.6645 36.186396
                                                   693.4955
    41.91439 29.01629
                           155.0658 53.974091
                                                 1029,6212
                                      8.874583
     5.88500 26.01833
                           140.4521
```

c) Analyse the plot and cluster centers:

The centers of those clusters are not overlapping. The averageSpeed and averageHeartRate are indicative of a distinct person's physical ability, meaning that it is probably one and the same person here, which is true as we only have 1 distinct user in this dataset.

Future reference: we could include a bigger population of users and include their age, weight (numeric vars) to perform cluster analysis that would show performance of different age groups/ weight groups.

The optimum number of clusters (line 662) was chosen as 6

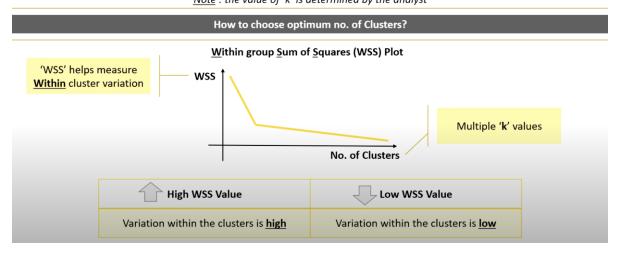


Rule:

What is 'K-Means'? – Choosing number of Clusters

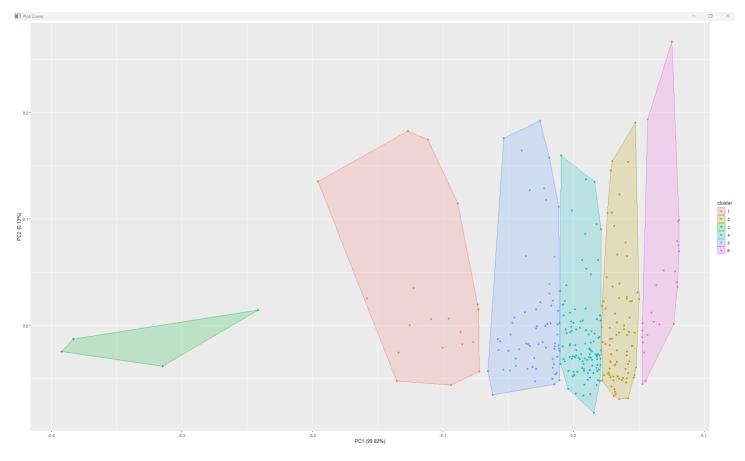
k-means clustering aims to partition ' \mathbf{n} ' observations into ' \mathbf{k} ' clusters.

Note: the value of ' \mathbf{k} ' is determined by the analyst



Source: https://www.youtube.com/watch?v=DWLoY6I6d34

Result:



d) When optimum is chosen as 4 we get more 'tight' groupings, where we can infer 4 types of performance at average same sppeeds: short ~ 20 min, medium ~ 40 min, long ~ 1h 20 min and very long ~ 2 h:



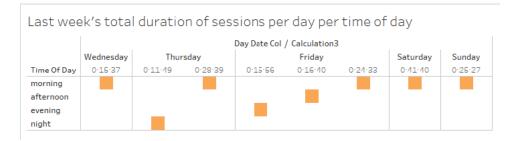
• Work was done on the following dataset:

https://github.com/alexbaar/Historical-Dataset-Analysis/blob/main/Data/data for Tableau dashboard.csv

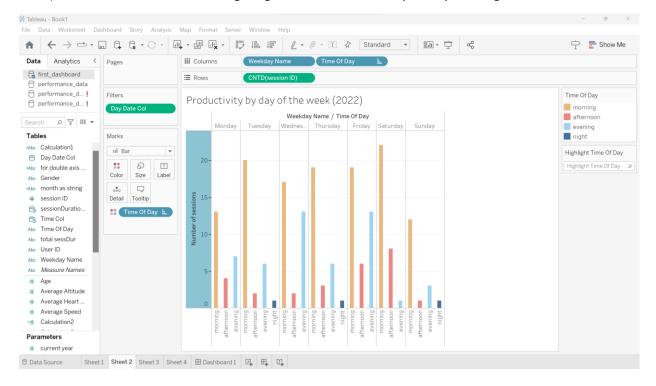
• The Tableau file can be found here:

https://github.com/alexbaar/Historical-Dataset-Analysis/tree/main/Tableau

- Dashboard results:
- a) Here, we can clearly see that morning sessions were the most frequent



b) We can conclude that mornings in general and Wednesday/Friday evenings featured the most activity



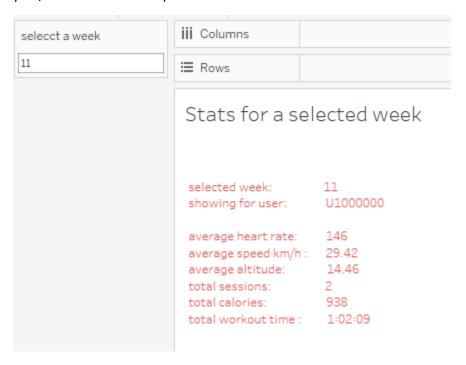
c) Current vs previous year comparison presenting monthly total time of sessions. The width of the lines depend on the number of individual sessions (thin = less, thick = more).



d) Select a week and show its stats

Note for future work:

Introduce second parameter 'year'. Adjust the 'selecct a week' parameter to accept values from 1 to 52 (1 year = 52 weeks). At the moment, a script was created to number all weeks from the dataset (across 2021 and 2022 which gave 84 weeks in total). So at the moment we can input any number from 1 to 84, but there is no distinction regarding the year/month that week is pulled from.



e) A comparison of daily average speed across a chosen month vs the month before the chosen one. Ideally we would get more datapoints so that line plot appears clearer.

Note for future work:

Find a way to display null/zero values for the days that no activity was recorded – include all dates in the data collection. Also change the x axis scale so that all days appear, even those with no values.



8. FLUTTER DASHBOARD VISUALIZATION

Set up FLUTTER:

Follow Victor Qin's 'Smart Bike Mobile App development environment setup' from User Manual.

If encountering the below error from step 'install Flutter-Firebase console on your machine':

```
firebase: The term 'firebase' is not recognized as the name of a cmdlet, function, script file, or operable program. Check the spelling of the name, or if a path was included, verify that the path is correct and try again.

At line:1 char:1

+ firebase --version

+ categoryInfo

: ObjectNotFound: (firebase:String) [], CommandNotFoundException

+ FullyQualifiedErrorId: CommandNotFoundException
```

Make sure the following conditions are met: (all should be executed in terminal)

- a) Check if the latest version of node.js LTS is installed. If in doubt, uninstall the current version and download the latest one, which is a compatible one with firebase.
- b) Reinstall firebase CLI:

npm uninstall -g firebase-tools

npm install -g firebase-tools

c) Set the execution policy and verify the installation. The desired output should be:

```
PS C:\Users\milly> Get-ExecutionPolicy
Restricted
PS C:\Users\milly> Set-ExecutionPolicy RemoteSigned
PS C:\Users\milly> firebase --version
13.0.2
```

d) Execute the below line. It will redirect you to firebase. Enter you login details.

firebase login

```
PS C:\Users\milly> firebase login
i Firebase optionally collects CLI and Emulator Suite usage and error reporting information to help improve
privacy policy (https://policies.google.com/privacy) and is not used to identify you.

Allow Firebase to collect CLI and Emulator Suite usage and error reporting information? Yes
i To change your data collection preference at any time, run 'firebase logout' and log in again.

Visit this URL on this device to log in:
https://accounts.google.com/o/oauth2/auth?client_id=563584335869-fgrhgmd47bqnekij5i8b5pr03ho849e6.apps.googl
gleapis.com%2Fauth%2Fcloudplatformprojects.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Ffirebase%20h
nse_type=code&state=670215369&redirect_uri=http%3A%2F%2Flocalhost%3A9005

Waiting for authentication...

+ Success! Logged in as o.bartosiak@gmail.com
```

e) Finally execute this command

dart pub global activate flutterfire_cli

Access the Mobile App files:

https://github.com/redbackoperations/Projects/tree/main/SmartBikeMobileApp/smart_bike_mobile_app

Helpful links:

https://www.youtube.com/watch?v=aCUM4r1ONhg	8:54
https://www.youtube.com/watch?v=GRQIYu6JxSg	8:38
https://www.youtube.com/watch?v=_V8eKsto3Ug	2:10:38

https://www.youtube.com/watch?v=KmYUE7Of5rU	9:35
https://www.youtube.com/watch?v=DWLoY6I6d34	5:11
https://www.youtube.com/watch?v=QnNOh-Wza_Q	3:24
Tableau:	
https://www.youtube.com/watch?v=Zb-2RR2VbJo	31:31
https://www.youtube.com/watch?v=2oO7lzWr0f0	12:50

Flutter:

https://www.youtube.com/playlist?list=PL4cUxeGkcC9jLYyp2Aoh6hcWuxFDX6PBJ 3:00:00