The data contains a total of 2864056 entries of time series data with 33 columns Entries are spaced by 0.01s

The variable we predict activityID, which has 13 different values.

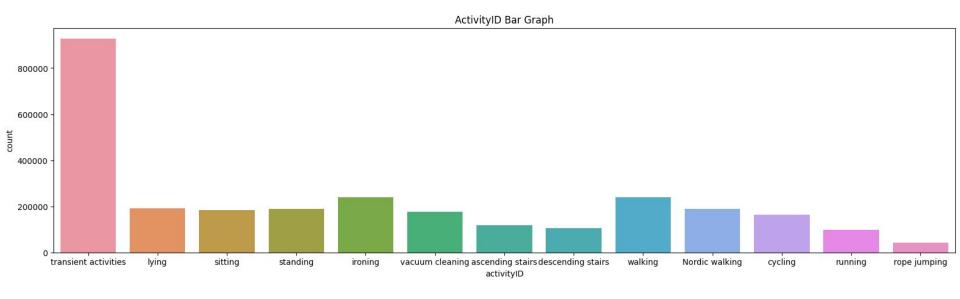
We are able to find 193 task switch of various time lengths

RangeIndex: 2864056 entries, 0 to 2864055 Data columns (total 33 columns):

Samples are float64

The histogram below displays the counts of each ActivityID label

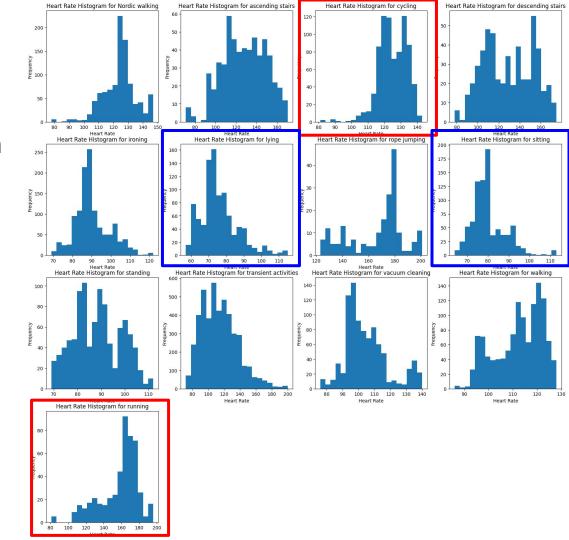
While 'transient activities' is the most common, most other labels have similar frequencies



We suspect heart rate has a high feature importance

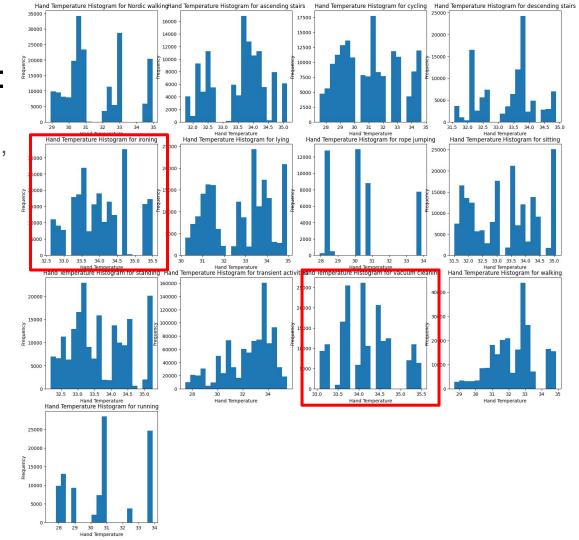
The heart rates for cycling and running are much higher than the heart rates for sitting and laying down.

Other activities are in between



In the case of hand temperature, most labels have ranges between 28°C and 35°C.

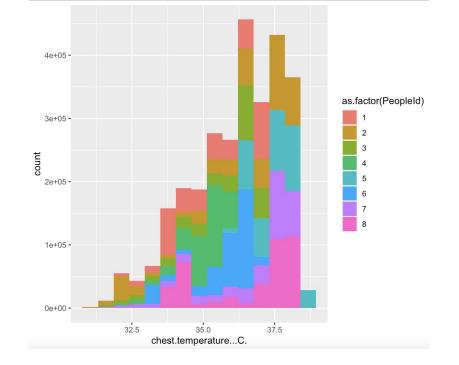
Hand temperatures for ironing and vacuuming are all greater than 32°C

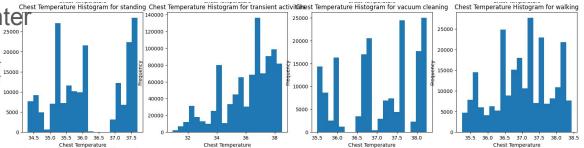


For chest temperature, some labels have isolated peaks

One possible explanation is that different people have different average chest temperatures

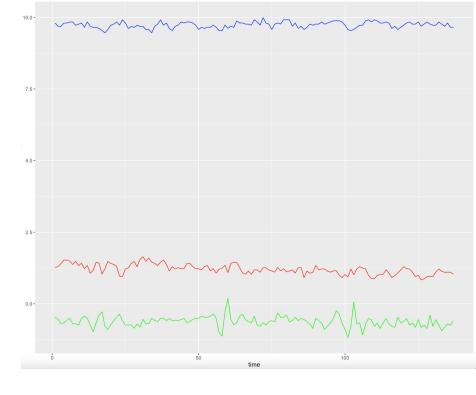
We can see that people 2, 5, 7, and 8 have chest temperatures above 37°C, while the rest center around 35°C.





Other features, like X, Y, and Z measurements of acceleration, gyroscope, and magnetosphere are less intuitive.

This graph explores X, Y, and Z chest acceleration in a time series of jump rope.



Notice high acceleration shown by the blue line, which is the Y acceleration: we can intuit this is the bouncing motion

Both X and Z are much lower, and signify slight motion forward/back and left/right

# Data Cleaning: A brief look at missing data →

Tiny fraction of missing heart\_rate data

We will drop these samples

chest gyroscope Z

chest magnetometer X chest magnetometer Y chest magnetometer Z ankle temperature (°C)

ankle acceleration Y ±16g

ankle acceleration Z ±16g

chest gyroscope X chest gyroscope Y

activityID heart rate

hand temperature (°C)

hand gyroscope X

hand gyroscope Y hand gyroscope Z hand magnetometer X hand magnetometer Y hand magnetometer Z

hand acceleration X ±16g hand acceleration Y ±16q hand acceleration Z ±16g

chest temperature (°C)

chest acceleration X ±16g chest acceleration Y ±16g chest acceleration Z ±16g

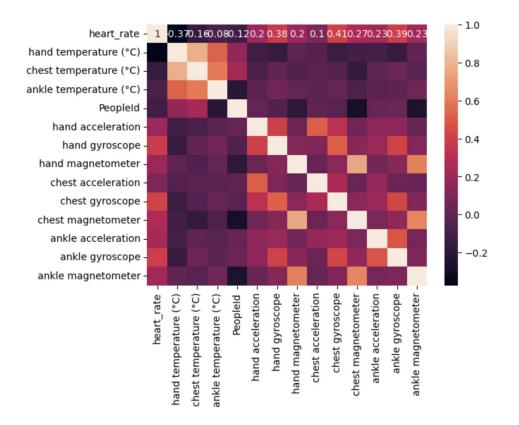
ankle acceleration X ±16g

0

46

## Data Cleaning:

Plotting feature correlation we shows very little collinearity, suggesting that we do not need to drop features.



### Data Sampling:

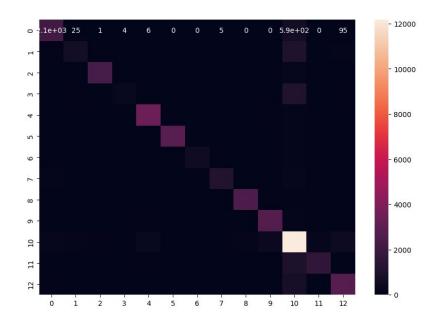
Because our cases are balanced, we do not expect to sample the data.

However, because we will be training a multiclass classifier using One vs. Rest, our data is naturally imbalanced.

To address this, we can oversample, sample with SMOTE, or apply weights to the 'One' class.

# Machine Learning Techniques

SVM: accuracy 0.8041

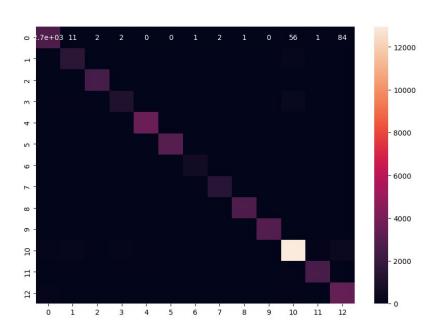


	precision	recall	f1-score	support	
Nordic walking	0.80	0.74	0.77	2838	
ascending stairs	0.71	0.32	0.44	1804	
cycling	0.93	0.92	0.92	2440	
descending stairs	0.81	0.17	0.29	1541	
ironing	0.88	0.95	0.91	3537	
lying	1.00	0.96	0.98	2933	
rope jumping	0.87	0.73	0.80	634	
running	0.96	0.75	0.84	1499	
sitting	0.95	0.92	0.94	2691	
standing	0.83	0.92	0.87	2850	
transient activities	0.70	0.87	0.78	13936	
vacuum cleaning	0.87	0.59	0.70	2658	
walking	0.79	0.76	0.78	3599	
accuracy			0.80	42960	
macro avg	0.85	0.74	0.77	42960	
weighted avg	0.81	0.80	0.79	42960	

# Machine Learning Techniques

Knn = 3

accuracy: 0.9387



	precision	recall	f1-score	support
	precision	recatt	11-30016	suppor c
Nordic walking	0.87	0.94	0.91	2838
ascending stairs	0.82	0.82	0.82	1804
cycling	0.97	0.99	0.98	2440
descending stairs	0.86	0.71	0.78	1541
ironing	0.97	0.99	0.98	3537
lying	1.00	0.99	1.00	2933
rope jumping	0.97	0.94	0.95	634
running	0.98	0.94	0.96	1499
sitting	0.99	0.99	0.99	2691
standing	0.98	0.99	0.98	2850
transient activities	0.94	0.93	0.93	13936
vacuum cleaning	0.96	0.94	0.95	2658
walking	0.87	0.93	0.90	3599
900				
accuracy			0.94	42960
macro avg	0.94	0.93	0.93	42960
weighted avg	0.94	0.94	0.94	42960