Machine Learning Based Activity Detection

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EE514: Data Analysis and Machine Learning

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1 Introduction

In this project, we're using data from smartphones and smartwatches to build a model that can tell when someone is sitting down. We'll be using various machine learning techniques to process this sensory data and build a model that can differentiate between sitting and other activities.

2 Approach

- Exploratory data analysis (EDA)
- Model training
- Model evaluation
- Model comparison
- Model fine-tuning
- Feature importance
- Cross-validation

3 Features

- The first row specifies the columns of the file.
- Every other row refers to an example from the user. The examples are sorted according to the primary key - the timestamp.
- The columns:
  - First column is 'timestamp'. This is represented as standard number of seconds since the epoch.
  - Second, come columns for the extracted features. Unavailable features are represented with 'nan'. The name of each feature contains reference to the sensor it was extracted from, in the form [sensor_name]:[feature_name]. The current version contains features from the following sensors, with sensor names:
    * raw_acc: Accelerometer from the phone. The 'raw' version of acceleration (as opposed to the decomposed versions of gravity and user-acceleration).

    * proc_gyro: Gyroscope from the phone. Processed version of gyroscope measurements (the OS calculates a version that removes drift).

        * raw_magnet: Magnetometer from the phone. Raw version (as opposed to bias-fixed version that the OS also provides).
        * watch_acceleration: Accelerometer from the watch.
        * watch_heading: Heading from the compass on the watch.
        * location: Location services. These features were extracted offline for every example from the sequence of latitude-longitude-altitude updates from the example's minute.
            · These features regard only to relative-location (not absolute location in the world) - meaning, they describe variability of movement within the minute.
        * location_quick_features: Location services. These features were calculated on the phone when data was collected.
            · These are available even in cases that the other location features are not because the user wanted to conceal their absolute location coordinates.
            · These quick features are very simple heuristics that approximate the more thoughtful offline features.
        * audio_naive: Microphone. These naive features are simply averages and standard deviations of the 13 MFCCs from the ~20sec recording window of every example.
        * discrete: Phone-state. These are binary indicators for the state of the phone.
            · Notice that time_of_day features are also considered phone-state features (also have prefix 'discrete:'), but their columns appear not right after the other 'discrete' columns.
        * lf_measurements: Various sensors that were recorded in low-frequency (meaning, once per example).
    – Third, come columns for the ground truth labels. The values are either 1 (label is relevant for the example), 0 (label is not relevant for the example), or 'nan' (label is considered 'missing' for this example).

Originally, users could only report 'positive' labels (in the original ExtraSensory paper, Vaizman2017a, we assumed that when a label was not reported it is a 'negative' example).

This cleaned version of the labels has the notion of 'missing labels'; Details about how we inferred missing label information is provided in the second paper, Vaizman2017b (see http://extrasensory.ucsd.edu for updated references).

The names of the labels have prefix 'label:'. After the prefix:

If the label name is all capitalized, it is an original label from the mobile app's interface and the values were taken from what the user originally reported.

If the label name begins with 'FIX_', this is a fixes/cleaned version of a corresponding label, meaning that the researchers fixed some of the values that were reported by users because of inconsistencies.

If the label name begins with 'OR_', this is a synthesized label, meaning it did not appear in the app's label menu, but rather the researchers created it as combination (using logical or) of other related labels.

If the label name begins with 'LOC_', this is a fixed/cleaned version of a corresponding label that was fixed by researchers based on absolute location. LOC_beach was based on original label 'AT_THE_BEACH'. LOC_home was based on original label 'AT_HOME'. LOC_main_workplace was based on original label 'AT_WORK'.

- Fourth, the last column is label_source, describing where the original labeling came from in the mobile app's interface. It has 8 possible values:
  * -1: The user did not report any labels for this example (notice, however, that this example may still have labeling for the 'LOC_' labels).
  * 0 : The user used the 'active feedback' interface (reporting immediate future). This example is the first in relevant minute sequence.
  * 1 : The user used the 'active feedback' interface. This example is a continuation of a sequence of minutes since the user started the reported context.
  * 2 : The user used the history interface to label an example from the past.
  * 3 : The user replied to a notification that simply asked to provide any labels.
  * 4 : The user replied to a notification that asked 'In the past [minutes] minutes were you still [recent context]?'. The user replied 'correct' on the phone.
  * 5 : The user replied to a notification that asked 'In the past [minutes] minutes were you still [recent context]?'. The user replied 'not exactly' and then corrected the context labels.
  * 6 : The user replied to a notification that asked 'In the past [minutes] minutes were you still [recent context]?'. The user replied 'correct' on the watch interface.

4 Tools Required

- pandas for data analysis
- NumPy for numerical operations
- Matplotlib/seaborn for plotting or data visualization.
- Scikit-Learn for machine learning modelling and evaluation.

5 Setting Up the Environment

[1]:
```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline

#Models
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
import xgboost as xgb

# Model Evaluators
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.model_selection import RandomizedSearchCV
```

```
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import accuracy_score, recall_score, precision_score,␣
 ↪f1_score, roc_auc_score
from sklearn.metrics import RocCurveDisplay


# Data Preprocessing
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler

# Saving and Loading Models
save_directory = 'model/'
import joblib
from joblib import dump
from joblib import load

# For reproducibility
np.random.seed(42)
```

5.1 Loading the Dataset

[2]:
```
cwd = "ExtraSensory.per_uuid_features_labels/"
```

5.2 Combining the entire datset into a single dataframe

The reason for this approach was that the initial exploratory analysis found a lot of missing values and it became increasingly difficult to model with a single csv file. Hence, I decided to combine the entire dataset, aiming to create a more comprehensive and cohesive data structure that would facilitate more effective modeling.

[3]:
```
all_files = sorted([file for file in os.listdir(cwd) if file.endswith('.
 ↪features_labels.csv.gz')])

def load_all_data():
    all_data = []
    for file_name in all_files:
        file_path = os.path.join(cwd, file_name)
        df = pd.read_csv(file_path)
        all_data.append(df)

    # Concatenate all dataframes
    combined_df = pd.concat(all_data, ignore_index=True)
    return combined_df
```

[4]:
```
# Load all data into a single dataframe
df = load_all_data()
```

[5]:
```
df.shape
```

[5]: (377346, 278)

6 Exploratory Data Analysis

The goal is to delve deeper into our dataset to better understand its nuances and characteristics. First step is to examine what kind of data do we have, is it categorical or numerical? Secondly we'll try and explore if there are any missing values. If yes, then how do we deal with. Finally, looking at the dataset, can we deduce some correlation between our feature and target variable.

[6]:
```
df.head()
```

[6]:
```
    timestamp  raw_acc:magnitude_stats:mean  raw_acc:magnitude_stats:std  \
0  1444079161                      0.996815                     0.003529
1  1444079221                      0.996864                     0.004172
2  1444079281                      0.996825                     0.003667
3  1444079341                      0.996874                     0.003541
4  1444079431                      0.997371                     0.037653

   raw_acc:magnitude_stats:moment3  raw_acc:magnitude_stats:moment4  \
0                        -0.002786                         0.006496
1                        -0.003110                         0.007050
2                         0.003094                         0.006076
3                         0.000626                         0.006059
4                         0.043389                         0.102332

   raw_acc:magnitude_stats:percentile25  raw_acc:magnitude_stats:percentile50  \
0                              0.995203                              0.996825
1                              0.994957                              0.996981
2                              0.994797                              0.996614
3                              0.995050                              0.996907
4                              0.995548                              0.996860

   raw_acc:magnitude_stats:percentile75  \
0                              0.998502
1                              0.998766
2                              0.998704
3                              0.998690
4                              0.998205

   raw_acc:magnitude_stats:value_entropy  \
0                               1.748756
1                               1.935573
2                               2.031780
3                               1.865318
4                               0.460806
```

```
   raw_acc:magnitude_stats:time_entropy  …  label:STAIRS_-_GOING_DOWN  \
0                              6.684605  …                       NaN
1                              6.684603  …                       NaN
2                              6.684605  …                       NaN
3                              6.684605  …                       NaN
4                              6.683904  …                       NaN

   label:ELEVATOR  label:OR_standing  label:AT_SCHOOL  label:PHONE_IN_HAND  \
0             NaN                0.0              NaN                  NaN
1             NaN                0.0              NaN                  NaN
2             NaN                0.0              NaN                  NaN
3             NaN                0.0              NaN                  NaN
4             NaN                0.0              NaN                  NaN

   label:PHONE_IN_BAG  label:PHONE_ON_TABLE  label:WITH_CO-WORKERS  \
0                 NaN                   1.0                    1.0
1                 NaN                   1.0                    1.0
2                 NaN                   1.0                    1.0
3                 NaN                   1.0                    1.0
4                 NaN                   1.0                    1.0

   label:WITH_FRIENDS  label_source
0                 NaN             2
1                 NaN             2
2                 NaN             2
3                 NaN             2
4                 NaN             2

[5 rows x 278 columns]
```

[7]:
```
df.columns.to_list()
```

[7]:
```
['timestamp',
 'raw_acc:magnitude_stats:mean',
 'raw_acc:magnitude_stats:std',
 'raw_acc:magnitude_stats:moment3',
 'raw_acc:magnitude_stats:moment4',
 'raw_acc:magnitude_stats:percentile25',
 'raw_acc:magnitude_stats:percentile50',
 'raw_acc:magnitude_stats:percentile75',
 'raw_acc:magnitude_stats:value_entropy',
 'raw_acc:magnitude_stats:time_entropy',
 'raw_acc:magnitude_spectrum:log_energy_band0',
 'raw_acc:magnitude_spectrum:log_energy_band1',
 'raw_acc:magnitude_spectrum:log_energy_band2',
 'raw_acc:magnitude_spectrum:log_energy_band3',
```

```
'raw_acc:magnitude_spectrum:log_energy_band4',
'raw_acc:magnitude_spectrum:spectral_entropy',
'raw_acc:magnitude_autocorrelation:period',
'raw_acc:magnitude_autocorrelation:normalized_ac',
'raw_acc:3d:mean_x',
'raw_acc:3d:mean_y',
'raw_acc:3d:mean_z',
'raw_acc:3d:std_x',
'raw_acc:3d:std_y',
'raw_acc:3d:std_z',
'raw_acc:3d:ro_xy',
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'proc_gyro:magnitude_stats:std',
'proc_gyro:magnitude_stats:moment3',
'proc_gyro:magnitude_stats:moment4',
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'proc_gyro:magnitude_stats:time_entropy',
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'proc_gyro:3d:mean_y',
'proc_gyro:3d:mean_z',
'proc_gyro:3d:std_x',
'proc_gyro:3d:std_y',
'proc_gyro:3d:std_z',
'proc_gyro:3d:ro_xy',
'proc_gyro:3d:ro_xz',
'proc_gyro:3d:ro_yz',
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'raw_magnet:magnitude_stats:std',
'raw_magnet:magnitude_stats:moment3',
'raw_magnet:magnitude_stats:moment4',
'raw_magnet:magnitude_stats:percentile25',
'raw_magnet:magnitude_stats:percentile50',
'raw_magnet:magnitude_stats:percentile75',
'raw_magnet:magnitude_stats:value_entropy',
```

```
'raw_magnet:magnitude_stats:time_entropy',
'raw_magnet:magnitude_spectrum:log_energy_band0',
'raw_magnet:magnitude_spectrum:log_energy_band1',
'raw_magnet:magnitude_spectrum:log_energy_band2',
'raw_magnet:magnitude_spectrum:log_energy_band3',
'raw_magnet:magnitude_spectrum:log_energy_band4',
'raw_magnet:magnitude_spectrum:spectral_entropy',
'raw_magnet:magnitude_autocorrelation:period',
'raw_magnet:magnitude_autocorrelation:normalized_ac',
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'raw_magnet:3d:mean_y',
'raw_magnet:3d:mean_z',
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'raw_magnet:3d:std_y',
'raw_magnet:3d:std_z',
'raw_magnet:3d:ro_xy',
'raw_magnet:3d:ro_xz',
'raw_magnet:3d:ro_yz',
'raw_magnet:avr_cosine_similarity_lag_range0',
'raw_magnet:avr_cosine_similarity_lag_range1',
'raw_magnet:avr_cosine_similarity_lag_range2',
'raw_magnet:avr_cosine_similarity_lag_range3',
'raw_magnet:avr_cosine_similarity_lag_range4',
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'watch_acceleration:magnitude_stats:std',
'watch_acceleration:magnitude_stats:moment3',
'watch_acceleration:magnitude_stats:moment4',
'watch_acceleration:magnitude_stats:percentile25',
'watch_acceleration:magnitude_stats:percentile50',
'watch_acceleration:magnitude_stats:percentile75',
'watch_acceleration:magnitude_stats:value_entropy',
'watch_acceleration:magnitude_stats:time_entropy',
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'watch_acceleration:magnitude_spectrum:log_energy_band1',
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'watch_acceleration:magnitude_autocorrelation:normalized_ac',
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'watch_acceleration:3d:mean_z',
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'watch_acceleration:3d:std_y',
'watch_acceleration:3d:std_z',
'watch_acceleration:3d:ro_xy',
```

```
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'watch_acceleration:spectrum:x_log_energy_band1',
'watch_acceleration:spectrum:x_log_energy_band2',
'watch_acceleration:spectrum:x_log_energy_band3',
'watch_acceleration:spectrum:x_log_energy_band4',
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'watch_acceleration:spectrum:y_log_energy_band1',
'watch_acceleration:spectrum:y_log_energy_band2',
'watch_acceleration:spectrum:y_log_energy_band3',
'watch_acceleration:spectrum:y_log_energy_band4',
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'watch_acceleration:spectrum:z_log_energy_band1',
'watch_acceleration:spectrum:z_log_energy_band2',
'watch_acceleration:spectrum:z_log_energy_band3',
'watch_acceleration:spectrum:z_log_energy_band4',
'watch_acceleration:relative_directions:avr_cosine_similarity_lag_range0',
'watch_acceleration:relative_directions:avr_cosine_similarity_lag_range1',
'watch_acceleration:relative_directions:avr_cosine_similarity_lag_range2',
'watch_acceleration:relative_directions:avr_cosine_similarity_lag_range3',
'watch_acceleration:relative_directions:avr_cosine_similarity_lag_range4',
'watch_heading:mean_cos',
'watch_heading:std_cos',
'watch_heading:mom3_cos',
'watch_heading:mom4_cos',
'watch_heading:mean_sin',
'watch_heading:std_sin',
'watch_heading:mom3_sin',
'watch_heading:mom4_sin',
'watch_heading:entropy_8bins',
'location:num_valid_updates',
'location:log_latitude_range',
'location:log_longitude_range',
'location:min_altitude',
'location:max_altitude',
'location:min_speed',
'location:max_speed',
'location:best_horizontal_accuracy',
'location:best_vertical_accuracy',
'location:diameter',
'location:log_diameter',
'location_quick_features:std_lat',
'location_quick_features:std_long',
'location_quick_features:lat_change',
'location_quick_features:long_change',
'location_quick_features:mean_abs_lat_deriv',
```

```
'location_quick_features:mean_abs_long_deriv',
'audio_naive:mfcc0:mean',
'audio_naive:mfcc1:mean',
'audio_naive:mfcc2:mean',
'audio_naive:mfcc3:mean',
'audio_naive:mfcc4:mean',
'audio_naive:mfcc5:mean',
'audio_naive:mfcc6:mean',
'audio_naive:mfcc7:mean',
'audio_naive:mfcc8:mean',
'audio_naive:mfcc9:mean',
'audio_naive:mfcc10:mean',
'audio_naive:mfcc11:mean',
'audio_naive:mfcc12:mean',
'audio_naive:mfcc0:std',
'audio_naive:mfcc1:std',
'audio_naive:mfcc2:std',
'audio_naive:mfcc3:std',
'audio_naive:mfcc4:std',
'audio_naive:mfcc5:std',
'audio_naive:mfcc6:std',
'audio_naive:mfcc7:std',
'audio_naive:mfcc8:std',
'audio_naive:mfcc9:std',
'audio_naive:mfcc10:std',
'audio_naive:mfcc11:std',
'audio_naive:mfcc12:std',
'audio_properties:max_abs_value',
'audio_properties:normalization_multiplier',
'discrete:app_state:is_active',
'discrete:app_state:is_inactive',
'discrete:app_state:is_background',
'discrete:app_state:missing',
'discrete:battery_plugged:is_ac',
'discrete:battery_plugged:is_usb',
'discrete:battery_plugged:is_wireless',
'discrete:battery_plugged:missing',
'discrete:battery_state:is_unknown',
'discrete:battery_state:is_unplugged',
'discrete:battery_state:is_not_charging',
'discrete:battery_state:is_discharging',
'discrete:battery_state:is_charging',
'discrete:battery_state:is_full',
'discrete:battery_state:missing',
'discrete:on_the_phone:is_False',
'discrete:on_the_phone:is_True',
'discrete:on_the_phone:missing',
```

```
'discrete:ringer_mode:is_normal',
'discrete:ringer_mode:is_silent_no_vibrate',
'discrete:ringer_mode:is_silent_with_vibrate',
'discrete:ringer_mode:missing',
'discrete:wifi_status:is_not_reachable',
'discrete:wifi_status:is_reachable_via_wifi',
'discrete:wifi_status:is_reachable_via_wwan',
'discrete:wifi_status:missing',
'lf_measurements:light',
'lf_measurements:pressure',
'lf_measurements:proximity_cm',
'lf_measurements:proximity',
'lf_measurements:relative_humidity',
'lf_measurements:battery_level',
'lf_measurements:screen_brightness',
'lf_measurements:temperature_ambient',
'discrete:time_of_day:between0and6',
'discrete:time_of_day:between3and9',
'discrete:time_of_day:between6and12',
'discrete:time_of_day:between9and15',
'discrete:time_of_day:between12and18',
'discrete:time_of_day:between15and21',
'discrete:time_of_day:between18and24',
'discrete:time_of_day:between21and3',
'label:LYING_DOWN',
'label:SITTING',
'label:FIX_walking',
'label:FIX_running',
'label:BICYCLING',
'label:SLEEPING',
'label:LAB_WORK',
'label:IN_CLASS',
'label:IN_A_MEETING',
'label:LOC_main_workplace',
'label:OR_indoors',
'label:OR_outside',
'label:IN_A_CAR',
'label:ON_A_BUS',
'label:DRIVE_-_I_M_THE_DRIVER',
'label:DRIVE_-_I_M_A_PASSENGER',
'label:LOC_home',
'label:FIX_restaurant',
'label:PHONE_IN_POCKET',
'label:OR_exercise',
'label:COOKING',
'label:SHOPPING',
'label:STROLLING',
```

```
 'label:DRINKING__ALCOHOL_',
 'label:BATHING_-_SHOWER',
 'label:CLEANING',
 'label:DOING_LAUNDRY',
 'label:WASHING_DISHES',
 'label:WATCHING_TV',
 'label:SURFING_THE_INTERNET',
 'label:AT_A_PARTY',
 'label:AT_A_BAR',
 'label:LOC_beach',
 'label:SINGING',
 'label:TALKING',
 'label:COMPUTER_WORK',
 'label:EATING',
 'label:TOILET',
 'label:GROOMING',
 'label:DRESSING',
 'label:AT_THE_GYM',
 'label:STAIRS_-_GOING_UP',
 'label:STAIRS_-_GOING_DOWN',
 'label:ELEVATOR',
 'label:OR_standing',
 'label:AT_SCHOOL',
 'label:PHONE_IN_HAND',
 'label:PHONE_IN_BAG',
 'label:PHONE_ON_TABLE',
 'label:WITH_CO-WORKERS',
 'label:WITH_FRIENDS',
 'label_source']
```

Looking at the above we can safely assume that we can use columns starting with prefix 'label' to correspond to our potential target(y) values. Let us explore this further.

6.1 Feature Engineering and Selection

[8]:
```python
label_columns = [col for col in df.columns if col.startswith('label:')]
label_df = df[label_columns]
```

[9]:
```python
label_df
```

[9]:
```
        label:LYING_DOWN  label:SITTING  label:FIX_walking  label:FIX_running  \
0                    0.0            1.0                0.0                NaN
1                    0.0            1.0                0.0                NaN
2                    0.0            1.0                0.0                NaN
3                    0.0            1.0                0.0                NaN
4                    0.0            1.0                0.0                NaN
…                      …              …                  …                  …
377341               NaN            NaN                NaN                NaN
```

```
377342             NaN            NaN                 NaN                 NaN
377343             NaN            NaN                 NaN                 NaN
377344             NaN            NaN                 NaN                 NaN
377345             NaN            NaN                 NaN                 NaN

        label:BICYCLING  label:SLEEPING  label:LAB_WORK  label:IN_CLASS  \
0                   NaN             0.0             NaN             0.0
1                   NaN             0.0             NaN             0.0
2                   NaN             0.0             NaN             0.0
3                   NaN             0.0             NaN             0.0
4                   NaN             0.0             NaN             0.0
…                    …              …              …              …
377341              NaN             NaN             NaN             NaN
377342              NaN             NaN             NaN             NaN
377343              NaN             NaN             NaN             NaN
377344              NaN             NaN             NaN             NaN
377345              NaN             NaN             NaN             NaN

        label:IN_A_MEETING  label:LOC_main_workplace  …  \
0                      1.0                       1.0  …
1                      1.0                       1.0  …
2                      1.0                       1.0  …
3                      1.0                       1.0  …
4                      1.0                       1.0  …
…                       …                        …  …
377341                 NaN                       NaN  …
377342                 NaN                       NaN  …
377343                 NaN                       NaN  …
377344                 NaN                       NaN  …
377345                 NaN                       NaN  …

        label:STAIRS_-_GOING_UP  label:STAIRS_-_GOING_DOWN  label:ELEVATOR  \
0                           NaN                        NaN             NaN
1                           NaN                        NaN             NaN
2                           NaN                        NaN             NaN
3                           NaN                        NaN             NaN
4                           NaN                        NaN             NaN
…                            …                         …              …
377341                      NaN                        NaN             NaN
377342                      NaN                        NaN             NaN
377343                      NaN                        NaN             NaN
377344                      NaN                        NaN             NaN
377345                      NaN                        NaN             NaN

        label:OR_standing  label:AT_SCHOOL  label:PHONE_IN_HAND  \
0                     0.0              NaN                  NaN
1                     0.0              NaN                  NaN
```

```
2                       0.0                NaN                     NaN
3                       0.0                NaN                     NaN
4                       0.0                NaN                     NaN
…                        …                  …                       …
377341                  NaN                NaN                     NaN
377342                  NaN                NaN                     NaN
377343                  NaN                NaN                     NaN
377344                  NaN                NaN                     NaN
377345                  NaN                NaN                     NaN

        label:PHONE_IN_BAG  label:PHONE_ON_TABLE  label:WITH_CO-WORKERS  \
0                      NaN                   1.0                    1.0
1                      NaN                   1.0                    1.0
2                      NaN                   1.0                    1.0
3                      NaN                   1.0                    1.0
4                      NaN                   1.0                    1.0
…                       …                    …                      …
377341                 NaN                   NaN                    NaN
377342                 NaN                   NaN                    NaN
377343                 NaN                   NaN                    NaN
377344                 NaN                   NaN                    NaN
377345                 NaN                   NaN                    NaN

        label:WITH_FRIENDS
0                      NaN
1                      NaN
2                      NaN
3                      NaN
4                      NaN
…                       …
377341                 NaN
377342                 NaN
377343                 NaN
377344                 NaN
377345                 NaN

[377346 rows x 51 columns]
```

Looking at the columns above our assumption seems to be right. We see that the columns with prefix "label:" are classified into 1's, 0's and NaN.

Let us calculate the pecentage of missing values which will help us understand the quality of our target variable.

[10]:
```
# Calculating the percentage of missing values for each 'label:' column
missing_percentages = df[label_columns].isna().sum() / len(df) * 100

# Sorting the percentages from lowest to highest
```

```python
sorted_missing_percentages = missing_percentages.sort_values()
sorted_missing_percentages
```

[10]:
```
label:LOC_home                   5.833373
label:SITTING                   18.749901
label:FIX_walking               18.749901
label:OR_standing               18.749901
label:LYING_DOWN                19.510741
label:EATING                    21.429934
label:SLEEPING                  24.401478
label:TALKING                   25.917858
label:AT_SCHOOL                 31.319267
label:OR_exercise               36.176082
label:COMPUTER_WORK             37.044781
label:IN_A_MEETING              38.726527
label:TOILET                    41.625723
label:COOKING                   44.521474
label:DRESSING                  44.902556
label:LOC_main_workplace        46.540575
label:BATHING_-_SHOWER          46.701436
label:GROOMING                  47.316256
label:OR_indoors                47.844684
label:WATCHING_TV               47.964998
label:SURFING_THE_INTERNET      48.937315
label:IN_A_CAR                  53.704028
label:ON_A_BUS                  55.205037
label:WITH_FRIENDS              56.163839
label:PHONE_ON_TABLE            56.956480
label:DRIVE_-_I_M_THE_DRIVER    56.998617
label:CLEANING                  57.752302
label:FIX_restaurant            58.239388
label:OR_outside                59.851701
label:PHONE_IN_HAND             62.447462
label:FIX_running               62.668214
label:SHOPPING                  63.218638
label:WASHING_DISHES            63.833193
label:BICYCLING                 64.175319
label:PHONE_IN_POCKET           64.392361
label:DRIVE_-_I_M_A_PASSENGER   65.260795
label:WITH_CO-WORKERS           70.302057
label:IN_CLASS                  71.097348
label:STAIRS_-_GOING_UP         74.922485
label:STAIRS_-_GOING_DOWN       74.979197
label:PHONE_IN_BAG              75.496759
label:DOING_LAUNDRY             80.396771
label:ELEVATOR                  81.132435
label:DRINKING__ALCOHOL_        81.241884
```

```
label:LOC_beach                  84.723834
label:AT_A_PARTY                 85.540326
label:STROLLING                  85.752863
label:LAB_WORK                   86.909892
label:AT_THE_GYM                 88.235466
label:AT_A_BAR                   91.196409
label:SINGING                    93.343775
dtype: float64
```

We see that our featureset has a lot of missing values. Therefore we will discard all those labels with 30% missing values and only focus on labels with fewer percentage of missing values.

Let us focus on predicting the label:SITING as it has fewer number of missing data.

[11]:
```
df
```

[11]:
```
         timestamp  raw_acc:magnitude_stats:mean  raw_acc:magnitude_stats:std  \
0       1444079161                      0.996815                     0.003529
1       1444079221                      0.996864                     0.004172
2       1444079281                      0.996825                     0.003667
3       1444079341                      0.996874                     0.003541
4       1444079431                      0.997371                     0.037653
…              …                         …                            …
377341  1444234779                      1.007886                     0.009355
377342  1444234839                      1.000400                     0.009068
377343  1444234899                      1.026223                     0.195112
377344  1444234959                      1.123513                     0.273450
377345  1444235019                      1.020624                     0.135672

        raw_acc:magnitude_stats:moment3  raw_acc:magnitude_stats:moment4  \
0                             -0.002786                         0.006496
1                             -0.003110                         0.007050
2                              0.003094                         0.006076
3                              0.000626                         0.006059
4                              0.043389                         0.102332
…                               …                                …
377341                         0.012618                         0.030905
377342                        -0.019631                         0.032762
377343                         0.255240                         0.379733
377344                         0.312818                         0.480787
377345                         0.104091                         0.185868

        raw_acc:magnitude_stats:percentile25  \
0                                   0.995203
1                                   0.994957
2                                   0.994797
3                                   0.995050
4                                   0.995548
```

```
…                                        …
377341                            1.005121
377342                            0.998186
377343                            0.983684
377344                            0.966631
377345                            0.915936

        raw_acc:magnitude_stats:percentile50  \
0                                 0.996825
1                                 0.996981
2                                 0.996614
3                                 0.996907
4                                 0.996860
…                                        …
377341                            1.008012
377342                            1.001128
377343                            1.000173
377344                            1.051232
377345                            1.018161

        raw_acc:magnitude_stats:percentile75  \
0                                 0.998502
1                                 0.998766
2                                 0.998704
3                                 0.998690
4                                 0.998205
…                                        …
377341                            1.010024
377342                            1.003113
377343                            1.030232
377344                            1.229708
377345                            1.115126

        raw_acc:magnitude_stats:value_entropy  \
0                                  1.748756
1                                  1.935573
2                                  2.031780
3                                  1.865318
4                                  0.460806
…                                         …
377341                             0.423861
377342                             0.768680
377343                             1.484173
377344                             1.808524
377345                             2.402200

        raw_acc:magnitude_stats:time_entropy  …  label:STAIRS_-_GOING_DOWN  \
```

```
0                                  6.684605  …                        NaN
1                                  6.684603  …                        NaN
2                                  6.684605  …                        NaN
3                                  6.684605  …                        NaN
4                                  6.683904  …                        NaN
…                                     …   …                         …
377341                             6.684569  …                        NaN
377342                             6.684569  …                        NaN
377343                             6.668006  …                        NaN
377344                             6.656521  …                        NaN
377345                             6.675872  …                        NaN

        label:ELEVATOR  label:OR_standing  label:AT_SCHOOL  \
0                  NaN                0.0              NaN
1                  NaN                0.0              NaN
2                  NaN                0.0              NaN
3                  NaN                0.0              NaN
4                  NaN                0.0              NaN
…                …                 …               …
377341             NaN                NaN              NaN
377342             NaN                NaN              NaN
377343             NaN                NaN              NaN
377344             NaN                NaN              NaN
377345             NaN                NaN              NaN

        label:PHONE_IN_HAND  label:PHONE_IN_BAG  label:PHONE_ON_TABLE  \
0                       NaN                 NaN                   1.0
1                       NaN                 NaN                   1.0
2                       NaN                 NaN                   1.0
3                       NaN                 NaN                   1.0
4                       NaN                 NaN                   1.0
…                     …                  …                    …
377341                  NaN                 NaN                   NaN
377342                  NaN                 NaN                   NaN
377343                  NaN                 NaN                   NaN
377344                  NaN                 NaN                   NaN
377345                  NaN                 NaN                   NaN

        label:WITH_CO-WORKERS  label:WITH_FRIENDS  label_source
0                         1.0                 NaN             2
1                         1.0                 NaN             2
2                         1.0                 NaN             2
3                         1.0                 NaN             2
4                         1.0                 NaN             2
…                       …                  …            …
377341                    NaN                 NaN            -1
377342                    NaN                 NaN            -1
```

```
377343                    NaN                NaN            -1
377344                    NaN                NaN            -1
377345                    NaN                NaN            -1

[377346 rows x 278 columns]
```

6.2 Correlation matrix

Let us try to deduce what features has some positive correlation with the behaviour “SITTING”.

[12]:
```python
# calculating the correlation matrix
correlation_matrix = df.corr()

# Since we are modellig only for SITTING, let us look as sitting_correlation
sitting_correlation = correlation_matrix['label:SITTING']

# Filter for only positive correlations
positive_sitting_correlation = sitting_correlation[(sitting_correlation > 0) &␣
 ↪(~sitting_correlation.index.str.startswith('label'))]
positive_sitting_correlation
```

[12]:
```
timestamp                                      0.033548
raw_acc:magnitude_stats:percentile25           0.043631
raw_acc:magnitude_stats:time_entropy           0.092854
raw_acc:magnitude_spectrum:log_energy_band0    0.090146
raw_acc:3d:ro_xy                               0.001802
                                                 …
lf_measurements:screen_brightness              0.204674
discrete:time_of_day:between9and15             0.210277
discrete:time_of_day:between12and18            0.283961
discrete:time_of_day:between15and21            0.251741
discrete:time_of_day:between18and24            0.140442
Name: label:SITTING, Length: 104, dtype: float64
```

[13]:
```python
sorted_positive_sitting_correlation = positive_sitting_correlation.
 ↪sort_values(ascending=False)
sorted_positive_sitting_correlation
```

[13]:
```
lf_measurements:light                  0.344915
location:max_speed                     0.301301
discrete:time_of_day:between12and18    0.283961
audio_naive:mfcc1:std                  0.265374
audio_naive:mfcc2:std                  0.265020
                                         …
raw_acc:3d:ro_xy                       0.001802
raw_magnet:3d:std_y                    0.001430
location:max_altitude                  0.001089
discrete:ringer_mode:missing           0.000666
```

```
discrete:wifi_status:missing           0.000509
Name: label:SITTING, Length: 104, dtype: float64
```

[14]:

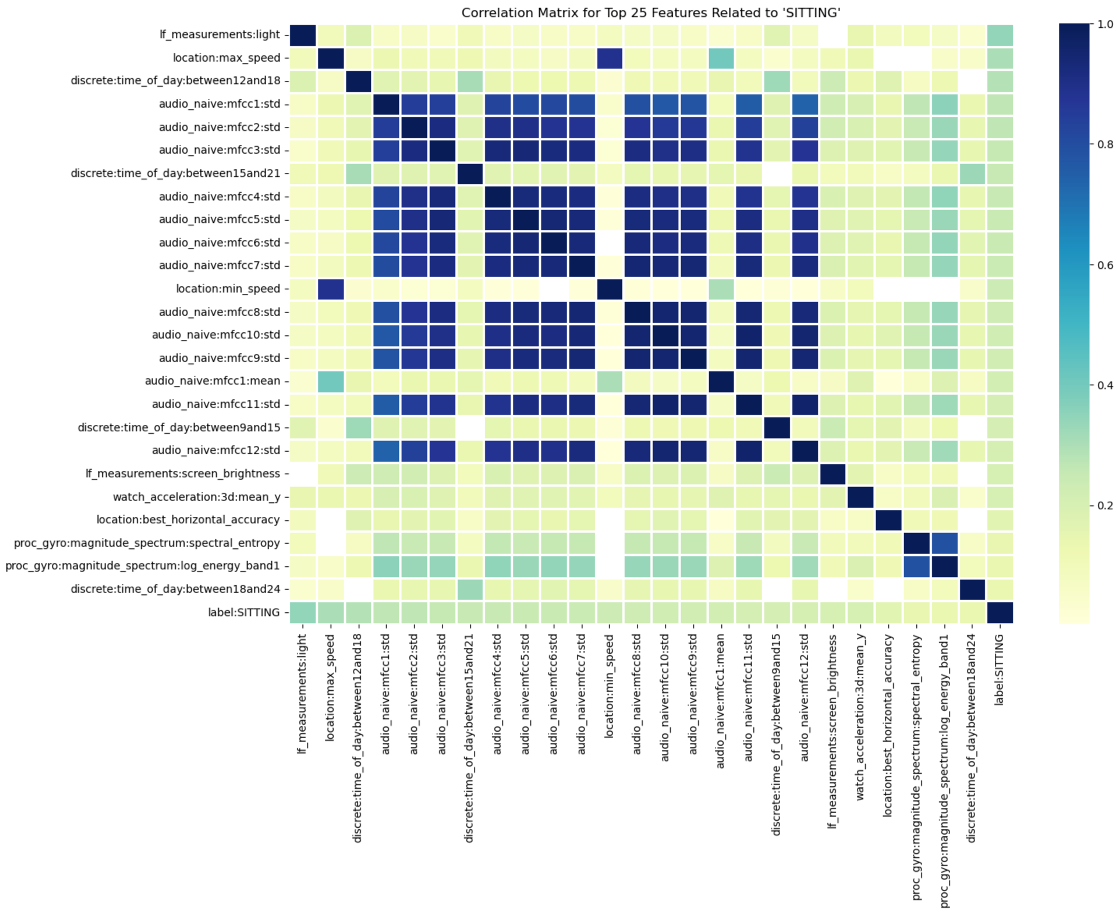
```
top_25_features = sorted_positive_sitting_correlation.head(25).index.tolist()

# Checking to see whether 'label:SITTING' has any correlation with these␣
↪features
top_25_features.append('label:SITTING')
filtered_df = df[top_25_features]

# We will filter it further for only positive correlation
correlation_matrix = filtered_df.corr()
correlation_matrix = correlation_matrix[correlation_matrix > 0]

plt.figure(figsize=(15, 10))
sns.heatmap(correlation_matrix,
            annot=False,
            linewidths=1,
            fmt=".2f",
            cmap="YlGnBu")

plt.title("Correlation Matrix for Top 25 Features Related to 'SITTING'")
plt.show()
```



Let us explore this further

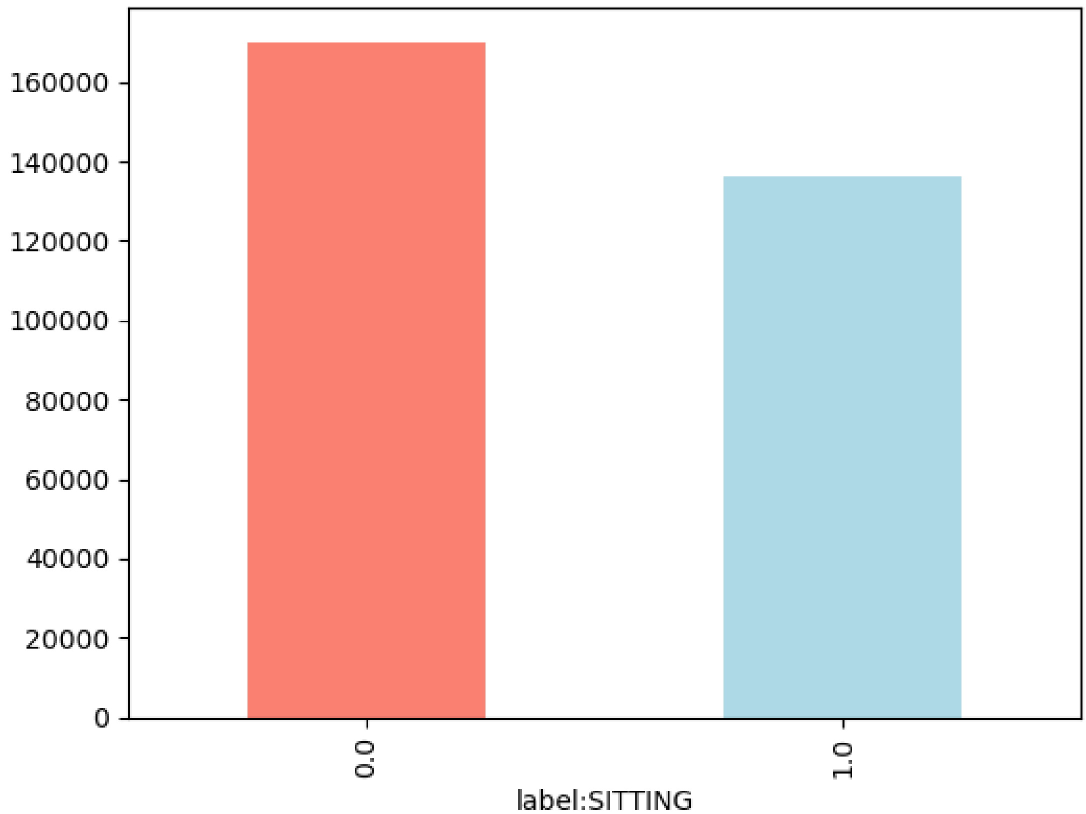
[15]:
```
df['label:SITTING']
```

[15]:
```
0         1.0
1         1.0
2         1.0
3         1.0
4         1.0
        …
377341    NaN
377342    NaN
377343    NaN
377344    NaN
377345    NaN
Name: label:SITTING, Length: 377346, dtype: float64
```

[16]:
```
df['label:SITTING'].value_counts()
```

[16]: label:SITTING
0.0   170238
1.0   136356
Name: count, dtype: int64

[17]:
```
df['label:SITTING'].value_counts().plot(kind="bar", color=["salmon",␣
↪"lightblue"]);
```



[18]:
```
df['label:SITTING'].info()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 377346 entries, 0 to 377345
Series name: label:SITTING
Non-Null Count   Dtype
--------------   -----
306594 non-null  float64
dtypes: float64(1)
memory usage: 2.9 MB
```

[19]:
```
df['label:SITTING'].isna().sum()
```

[19]: 70752

We can see we have 70752 missing values which we need to deal with.

[20]:
```
df['label:SITTING'].describe()
```

[20]:
```
count    306594.000000
mean          0.444745
std           0.496938
min           0.000000
25%           0.000000
50%           0.000000
75%           1.000000
max           1.000000
Name: label:SITTING, dtype: float64
```

7 Data Cleaning and Preprocessing

7.1 Handling Missing Data

Removing rows with missing values in target column(SITTING)

[21]:
```
df_cleaned = filtered_df.dropna(subset=['label:SITTING'])
```

[22]:
```
df_cleaned['label:SITTING'].isna().sum()
```

[22]: 0

7.2 Feature and Target Selection

[23]:
```
X = df_cleaned.drop('label:SITTING', axis=1)  # Features
y = df_cleaned['label:SITTING']               # Target
```

[24]:
```
X.shape
```

[24]: (306594, 25)

[25]:
```
X
```

[25]:
```
        lf_measurements:light  location:max_speed  \
0                         NaN                 NaN
1                         NaN                 NaN
2                         NaN                 NaN
3                         NaN                 NaN
4                         NaN                 NaN
…                           …                   …
377321                    NaN                1.74
377322                    NaN                3.48
```

```
377323                    NaN                2.68
377324                    NaN                2.24
377325                    NaN                1.37

        discrete:time_of_day:between12and18  audio_naive:mfcc1:std  \
0                                       1.0               1.271966
1                                       1.0               1.232031
2                                       1.0               1.186965
3                                       1.0               1.410698
4                                       1.0               2.147232
…                                       …                  …
377321                                  0.0               1.125063
377322                                  0.0               1.184854
377323                                  0.0               1.205948
377324                                  0.0               0.691122
377325                                  0.0               0.654368

        audio_naive:mfcc2:std  audio_naive:mfcc3:std  \
0                    1.177478               0.670053
1                    1.098946               0.669467
2                    1.251340               0.803958
3                    1.111916               0.821571
4                    1.251696               0.902605
…                    …                      …
377321               0.728020               0.482000
377322               0.733604               0.500369
377323               0.795810               0.465592
377324               0.425398               0.369699
377325               0.539415               0.381460

        discrete:time_of_day:between15and21  audio_naive:mfcc4:std  \
0                                       0.0               0.389200
1                                       0.0               0.499003
2                                       0.0               0.546688
3                                       0.0               0.519879
4                                       0.0               0.777665
…                                       …                  …
377321                                  0.0               0.373640
377322                                  0.0               0.424783
377323                                  0.0               0.366454
377324                                  0.0               0.289125
377325                                  0.0               0.321242

        audio_naive:mfcc5:std  audio_naive:mfcc6:std  …  \
0                    0.535904               0.468701  …
1                    0.584068               0.525900  …
2                    0.562475               0.559488  …
```

```
3                    0.572094                0.591143  …
4                    0.678277                0.652441  …
…                       …                     …   …
377321               0.286663                0.242171  …
377322               0.346504                0.271555  …
377323               0.303812                0.252889  …
377324               0.310188                0.238018  …
377325               0.243568                0.250475  …

        audio_naive:mfcc1:mean  audio_naive:mfcc11:std  \
0                    -0.012806                0.416881
1                     1.294372                0.362252
2                     1.309082                0.430171
3                     0.182373                0.379887
4                     0.908387                0.393817
…                        …                      …
377321                1.603140                0.213801
377322                1.690882                0.183018
377323                1.928444                0.198836
377324               -0.155248                0.175390
377325                0.923950                0.207095

        discrete:time_of_day:between9and15  audio_naive:mfcc12:std  \
0                                      1.0                0.263832
1                                      1.0                0.298252
2                                      1.0                0.330055
3                                      1.0                0.389737
4                                      1.0                0.331128
…                                      …                      …
377321                                 0.0                0.186613
377322                                 1.0                0.178549
377323                                 1.0                0.207751
377324                                 1.0                0.179356
377325                                 1.0                0.196992

        lf_measurements:screen_brightness  watch_acceleration:3d:mean_y  \
0                                0.381436                    -55.824000
1                                0.381436                    -56.096000
2                                0.381436                    -57.696000
3                                0.381436                    -56.400000
4                                0.381436                   -101.187368
…                                   …                            …
377321                           0.000015                           NaN
377322                           0.000015                           NaN
377323                           0.000015                           NaN
377324                           0.456982                           NaN
377325                           0.987446                           NaN
```

```
        location:best_horizontal_accuracy  \
0                                    65.0
1                                    65.0
2                                    65.0
3                                    65.0
4                                    65.0
…                                   …
377321                                5.0
377322                                5.0
377323                                5.0
377324                                5.0
377325                                5.0

        proc_gyro:magnitude_spectrum:spectral_entropy  \
0                                            1.766920
1                                            1.455363
2                                            1.848755
3                                            1.726047
4                                            3.425678
…                                               …
377321                                       1.321307
377322                                       1.315108
377323                                       1.389615
377324                                       1.223915
377325                                       1.684402

        proc_gyro:magnitude_spectrum:log_energy_band1  \
0                                            2.818909
1                                            2.153223
2                                            3.366933
3                                            3.325518
4                                            3.912588
…                                               …
377321                                       0.788453
377322                                       0.122612
377323                                       0.843170
377324                                       2.344227
377325                                       3.560600

        discrete:time_of_day:between18and24
0                                      0.0
1                                      0.0
2                                      0.0
3                                      0.0
4                                      0.0
…                                     …
```

```
377321                                        0.0
377322                                        0.0
377323                                        0.0
377324                                        0.0
377325                                        0.0

[306594 rows x 25 columns]
```

[26]:
```
y
```

[26]:
```
0         1.0
1         1.0
2         1.0
3         1.0
4         1.0
         …
377321    0.0
377322    0.0
377323    0.0
377324    0.0
377325    0.0
Name: label:SITTING, Length: 306594, dtype: float64
```

7.3 Data Transformation and Scaling

Data imputation standardizes our featureset, handling missing data effectively.

[27]:
```
imputer = SimpleImputer(strategy='mean')
X = imputer.fit_transform(X)
```

Scaling ensures that all features contribute equally to the model thereby avoiding skewed results.

[28]:
```
scaler = StandardScaler()
X = scaler.fit_transform(X)
```

7.4 Splitting the Dataset

[29]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

8 Model Selection

We will choose a diverse range of models to check each algorithms' effectiveness on our dataset.

[30]:
```
# Models dictionary
models = {
    "Logistic Regression": LogisticRegression(),
    "KNN": KNeighborsClassifier(),
    "Random Forest": RandomForestClassifier(),
```

```
    "Decision Tree": DecisionTreeClassifier(),
    "XGBoost": xgb.XGBClassifier()
}
```

Defining a function that loops through each model and outputs its performance.

[31]:
```
# Function to fit and score models
def fit_and_score(models, X_train, X_test, y_train, y_test):
    model_scores = {}
    for name, model in models.items():
        model.fit(X_train, y_train)
        model_scores[name] = model.score(X_test, y_test)
    return model_scores
```

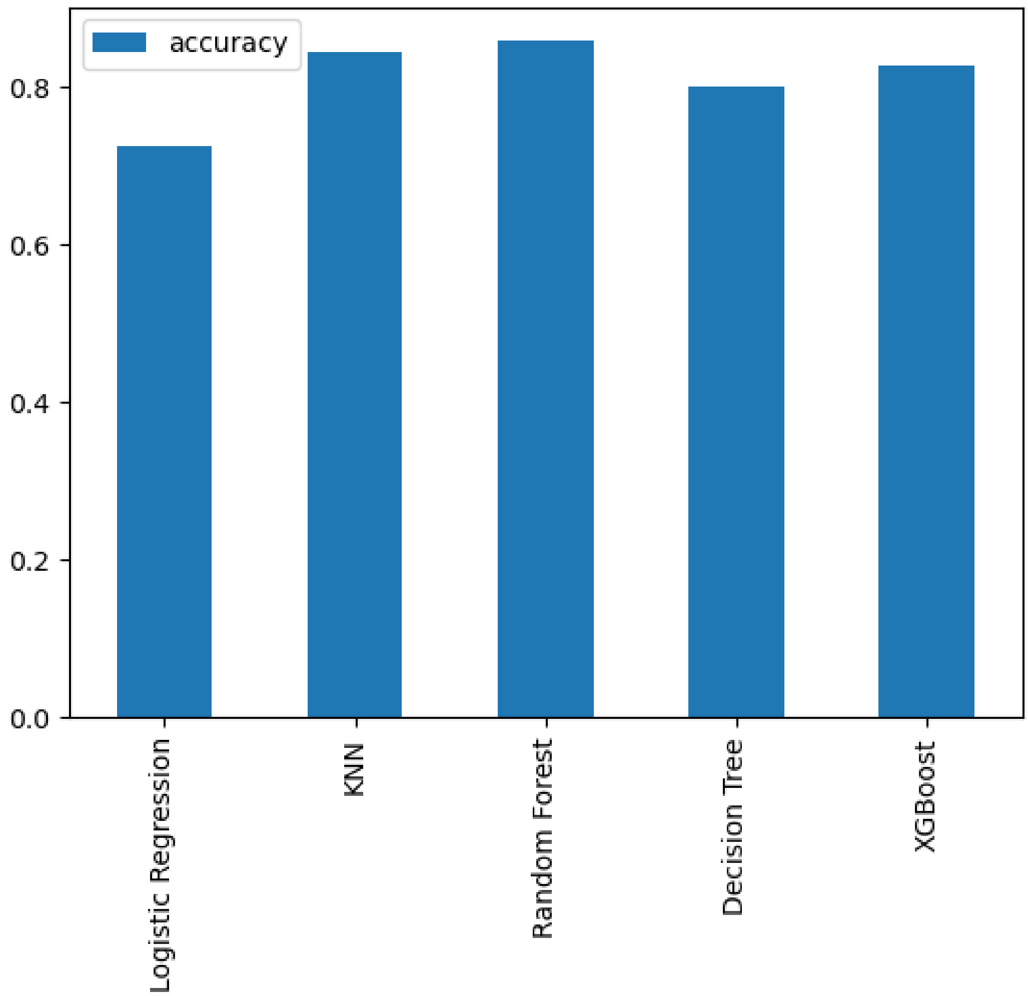
9 Model Training and Evaluation

[32]:
```
model_scores = fit_and_score(models=models,
                             X_train=X_train,
                             X_test=X_test,
                             y_train=y_train,
                             y_test=y_test)
model_scores
```

[32]:
```
{'Logistic Regression': 0.7262838598150655,
 'KNN': 0.8450072571307425,
 'Random Forest': 0.8593258207081003,
 'Decision Tree': 0.8020841827166131,
 'XGBoost': 0.8283892431383421}
```

Comparing and plotting each model performance.

[33]:
```
model_compare = pd.DataFrame(model_scores, index=['accuracy'])
model_compare.T.plot.bar();
```



We see that RandomForestClassifier performs that best followed by KNN in our baseline performance test. We'll discard the rest and try to further optimize the performance of the two.

10 Model Optimization and Hyperparameter Tuning

10.1 Tuning KNeighborsClassifier by hand

[ ]:
```
# # Creating a list of train scores
# train_scores = []

# # Creating a list of test scores
# test_scores = []

# neighbors = range(1, 11) # 1 to 10

# knn = KNeighborsClassifier()
```

```
# # Loop through different neighbors
# for i in neighbors:
#     knn.set_params(n_neighbors = i) # set neighbors value
#     knn.fit(X_train, y_train)
#     train_scores.append(knn.score(X_train, y_train))
#     test_scores.append(knn.score(X_test, y_test))
```

[ ]:
```
# # Save the train scores
# dump(train_scores, save_directory + 'knn_train_scores.joblib')
# print('Train scores saved'))

# # Save the test scores
# dump(test_scores, save_directory + 'knn_test_scores.joblib')
# print('Test scores saved'))

# # Save the KNN model
# dump(knn, save_directory + 'knn_model.joblib')
# print('KNN model saved'))
```

[34]:
```
# Load the train scores
train_scores = load(save_directory + 'knn_train_scores.joblib')
print('Train scores loaded')

# Load the test scores
test_scores = load(save_directory + 'knn_test_scores.joblib')
print('Test scores loaded')

# Load the KNN model
knn = load(save_directory + 'knn_model.joblib')
print('KNN model loaded')
```

```
Train scores loaded
Test scores loaded
KNN model loaded
```

[35]:
```
train_scores
```

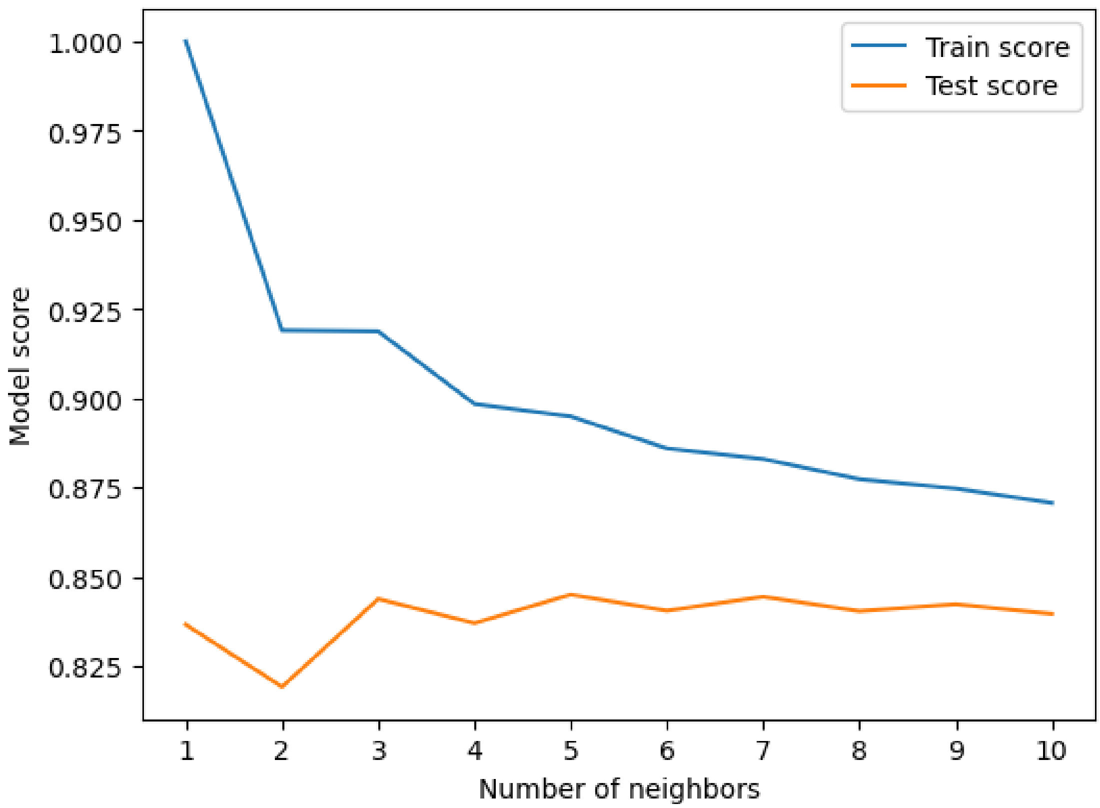
[35]:
```
[0.9998613800835796,
 0.9189399653450209,
 0.9186668025685455,
 0.8983467536438692,
 0.8948731016206299,
 0.8859158087860565,
 0.8829436346957497,
 0.8773050657425339,
 0.8746875955560086,
 0.8706513097543573]
```

[36]:
```
test_scores
```

[36]:
```
[0.8365922471012247,
 0.8191751333191996,
 0.8437678370488756,
 0.836999951075523,
 0.8450072571307425,
 0.840473588936545,
 0.8444038552487809,
 0.8403594318237414,
 0.8423001027414015,
 0.8396092565110325]
```

[37]:
```
neighbors = range(1, 11) # 1 to 10
plt.plot(neighbors, train_scores, label="Train score")
plt.plot(neighbors, test_scores, label="Test score")
plt.xticks(np.arange(1, 11, 1))
plt.xlabel("Number of neighbors")
plt.ylabel("Model score")
plt.legend()
```

[37]:
```
<matplotlib.legend.Legend at 0x7f7169d53410>
```



[38]:
```python
print(f"Maximum KNN score on the test data: {max(test_scores)*100:.4f}%")
```

```
Maximum KNN score on the test data: 84.5007%
```

[39]:
```python
model_scores
```

[39]:
```
{'Logistic Regression': 0.7262838598150655,
 'KNN': 0.8450072571307425,
 'Random Forest': 0.8593258207081003,
 'Decision Tree': 0.8020841827166131,
 'XGBoost': 0.8283892431383421}
```

Looking at the graph, n_neighbors = 5 seems best. But when we compare it with our base model we do not see any improvement in accuracy. So we will stop tuning it further.

Let us try and tune our best model i.e RandomForest Classifier

10.2 Tuning Random Forest Classifier with RandomizedSearchCV

[ ]:
```python
# rf_grid = {
#     "n_estimators": np.arange(10, 500, 50),
#     "max_depth": [None, 3, 5, 10],
#     "min_samples_split": np.arange(2, 20, 2),
#     "min_samples_leaf": np.arange(1, 20, 2)
# }
```

[ ]:
```python
# rs_rf = RandomizedSearchCV(RandomForestClassifier(),
#                            param_distributions=rf_grid,
#                            cv=3,
#                            n_iter=10,
#                            verbose=True,
#                            n_jobs=-1)

# # Fit random hyperparameter search model
# rs_rf.fit(X_train, y_train);
```

[ ]:
```python
# # Save the RandomizedSearchCV object for RandomForestClassifier
# dump(rs_rf, save_directory + 'random_forest_random_search_model.joblib')
# print('RandomizedSearchCV model saved'))
```

[40]:
```python
# Load the RandomizedSearchCV object for RandomForestClassifier
rs_rf = load(save_directory + 'random_forest_random_search_model.joblib')
print('RandomizedSearchCV object for RandomForestClassifier loaded')
```

```
RandomizedSearchCV object for RandomForestClassifier loaded
```

[41]:
```python
# Best parameters
rs_rf.best_params_
```

[41]:
```
{'n_estimators': 310,
 'min_samples_split': 4,
 'min_samples_leaf': 11,
 'max_depth': None}
```

[42]:
```
# Evaluating the randomized search random forest model
rs_rf.score(X_test, y_test)
```

[42]:
```
0.8445017042026126
```

[43]:
```
model_scores
```

[43]:
```
{'Logistic Regression': 0.7262838598150655,
 'KNN': 0.8450072571307425,
 'Random Forest': 0.8593258207081003,
 'Decision Tree': 0.8020841827166131,
 'XGBoost': 0.8283892431383421}
```

We don't see any improvement in scores after hyperparamter tuning. Infact we observe that the baseline model performs better. Hence, we will stop modeling further.

11 Final Model Evaluation

We'll make predictions on the test data

[44]:
```
y_preds = rs_rf.predict(X_test)
```

[45]:
```
y_preds
```

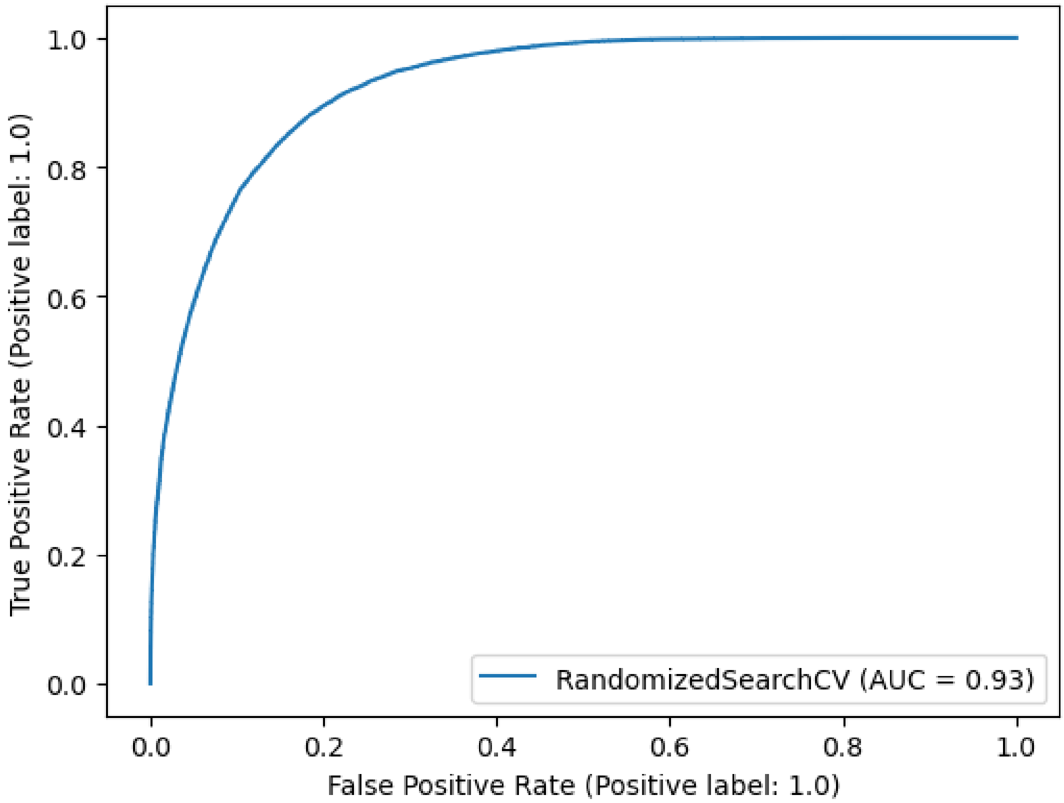
[45]:
```
array([1., 1., 1., …, 0., 1., 0.])
```

[46]:
```
y_test
```

[46]:
```
287855    1.0
19744     1.0
54685     1.0
261262    0.0
139215    1.0
         …
326981    0.0
333000    0.0
62508     0.0
197346    1.0
120297    1.0
Name: label:SITTING, Length: 61319, dtype: float64
```

11.1 ROC Curve

[47]:
```
RocCurveDisplay.from_estimator(estimator=rs_rf,
                               X=X_test,
                               y=y_test);
```



This is great. Our model has a area under the curve (AUC) of 0.93, suggesting that the model has a strong ability to distinguish between the positive and negative classes. The curve approaches the top left corner of the graph, showing a low false positive rate and a high true positive rate.

11.2 Confusion Matrix

[48]:
```
print(confusion_matrix(y_test, y_preds))
```

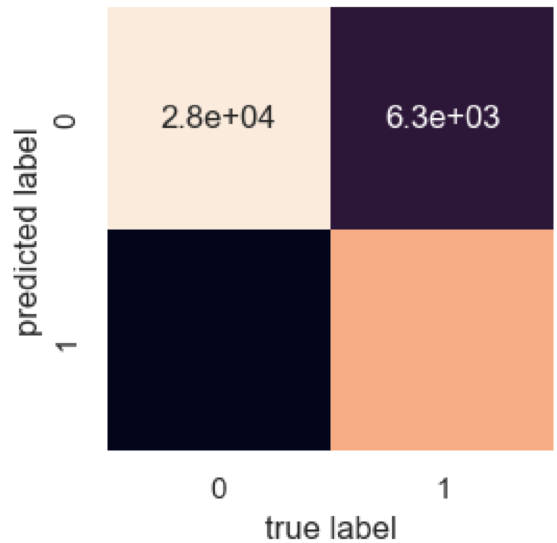
```
[[27887  6257]
 [ 3278 23897]]
```

[49]:
```
sns.set(font_scale=1) # Increase font size

def plot_conf_mat(y_test, y_preds):
    fig, ax = plt.subplots(figsize=(3, 3))
    ax = sns.heatmap(confusion_matrix(y_test, y_preds),
```

```
                    annot=True,
                    cbar=False)
    plt.xlabel("true label")
    plt.ylabel("predicted label")

plot_conf_mat(y_test, y_preds)
```



The confusion matrix shows that the model is pretty good at guessing right (27887)when something wasn't true and got it right 23897 times when something was true. However, there are 6257 false positives and 3278 false negatives thereby indicating areas for improvement

11.3 Classification Report

[50]:
```
print(classification_report(y_test, y_preds))
```

```
              precision    recall  f1-score   support

         0.0       0.89      0.82      0.85     34144
         1.0       0.79      0.88      0.83     27175

    accuracy                           0.84     61319
   macro avg       0.84      0.85      0.84     61319
weighted avg       0.85      0.84      0.84     61319
```

12 Evaluation metrics using cross-validation

[51]:
```
rs_rf.best_params_
```

[51]:
```
{'n_estimators': 310,
 'min_samples_split': 4,
 'min_samples_leaf': 11,
 'max_depth': None}
```

[52]:
```
## Instantiate best model with best hyperparameters
clf = RandomForestClassifier(n_estimators = 310,
                   min_samples_split = 4,
                   min_samples_leaf = 11,
                   max_depth = None)
```

12.1 Mean Cross Validated Accuracy Score

[ ]:
```
# # Cross-validated accuracy score
# cv_acc = np.mean(cross_val_score(clf,
#                            X,a
#                            y,
#                            cv=5, # 5-fold cross-validation
#                            scoring="accuracy")) # accuracy as scoring
# cv_acc
```

[ ]:
```
# # Save the cv_acc value
# dump(cv_acc, save_directory + 'cv_accuracy.joblib')
# print('Cross-validation accuracy saved'))
```

[53]:
```
# Load the saved cv_acc value
cv_acc = load(save_directory + 'cv_accuracy.joblib')
print('Cross-validation accuracy:', cv_acc)
```

```
Cross-validation accuracy: 0.750106042581627
```

12.2 Mean Cross Validated Precsion Score

[ ]:
```
# # Cross-validated precision score
# cv_precision = np.mean(cross_val_score(clf,
#                                        X,
#                                        y,
#                                        cv=5, # 5-fold cross-validation
#                                        scoring="precision"))
# cv_precision
```

[ ]:
```
# # Save the cv_precision value
# dump(cv_precision, save_directory + 'cv_precision.joblib')
# print('Cross-validation precision score saved'))
```

[54]:
```python
# Load the saved cv_precision value
cv_precision = load(save_directory + 'cv_precision.joblib')
print('Cross-validation precision score:', cv_precision)
```

```
Cross-validation precision score: 0.6926955016104406
```

12.3 Mean Cross Validated Recall Score

[ ]:
```python
# # Cross-validated recall score
# cv_recall = np.mean(cross_val_score(clf,
#                                     X,
#                                     y,
#                                     cv=5, # 5-fold cross-validation
#                                     scoring="recall"))
# cv_recall
```

[ ]:
```python
# # Save the cv_recall value
# dump(cv_recall, save_directory + 'cv_recall.joblib')
# print('Cross-validation recall score saved'))
```

[55]:
```python
# Load the saved cv_recall value
cv_recall = load(save_directory + 'cv_recall.joblib')
print('Cross-validation recall score:', cv_recall)
```

```
Cross-validation recall score: 0.789316239417369
```

12.4 Mean Cross Validated F1 Score

[ ]:
```python
# # Cross-validated F1 score
# cv_f1 = np.mean(cross_val_score(clf,
#                                 X,
#                                 y,
#                                 cv=5,
#                                 scoring="f1"))
# cv_f1
```

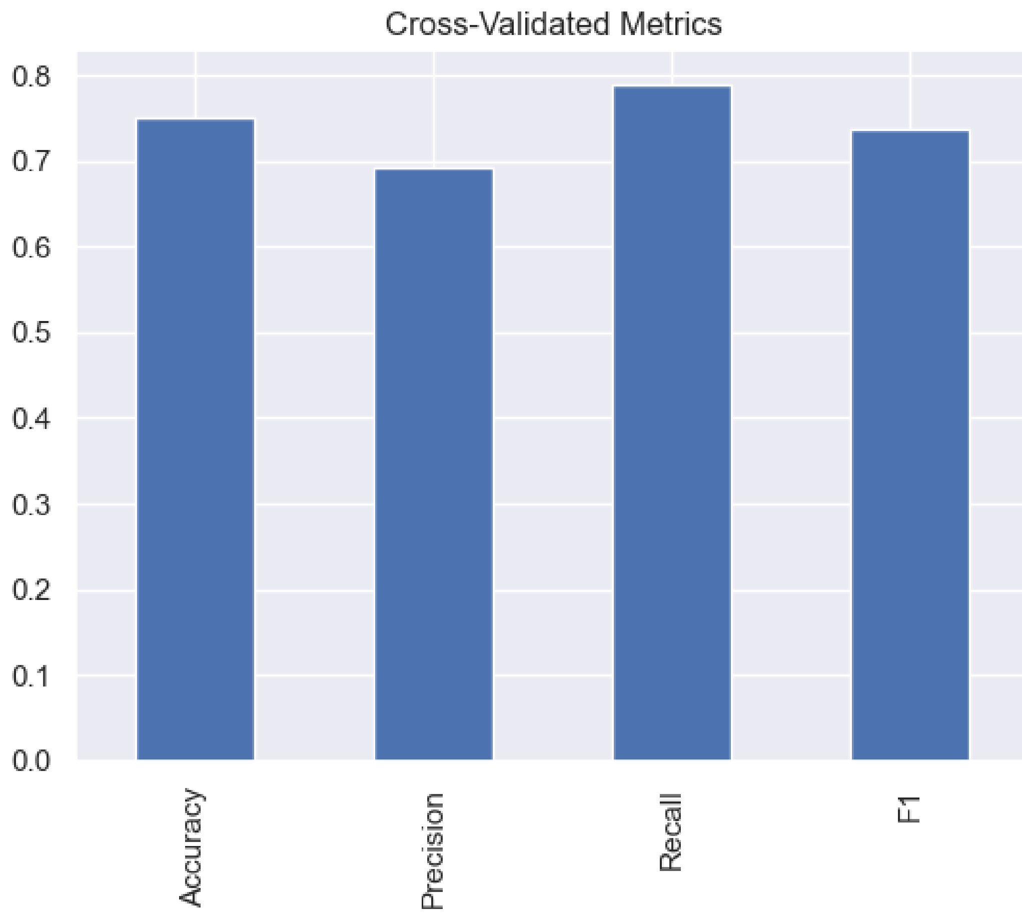
[ ]:
```python
# # Save the cv_f1 value
# dump(cv_f1, save_directory + 'cv_f1.joblib')
# print('Cross-validation F1 score saved'))
```

[56]:
```python
# Load the saved cv_f1 value
cv_f1 = load(save_directory + 'cv_f1.joblib')
print('Cross-validation F1 score:', cv_f1)
```

```
Cross-validation F1 score: 0.7379484934145412
```

12.5 Visualizing cross-validated metrics

[57]:
```
cv_metrics = pd.DataFrame({"Accuracy": cv_acc,
                            "Precision": cv_precision,
                            "Recall": cv_recall,
                            "F1": cv_f1},
                          index=[0])
cv_metrics.T.plot.bar(title="Cross-Validated Metrics", legend=False);
```



13 Feature Importance Analysis

Let's take a look at which parts of the data have the biggest impact on what the model predicts.

[58]:
```
# Fit an instance of RandomForestClassifier
clf.fit(X_train, y_train);
```

[59]:
```
feature_importances = clf.feature_importances_
```

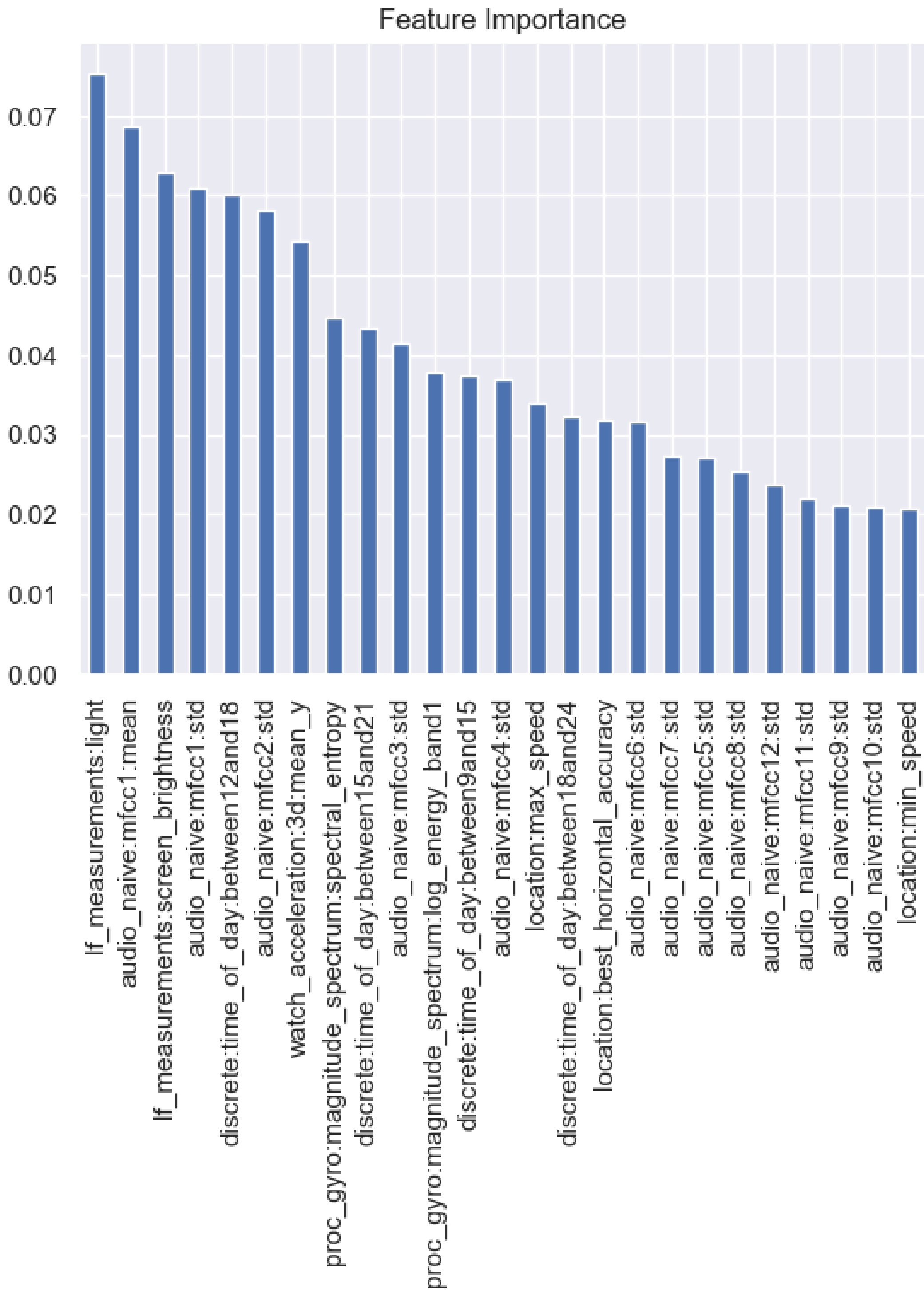
[60]:
```
features_dict = dict(zip(df_cleaned.columns, feature_importances))
```

[61]:
```
features_dict
```

[61]:
```
{'lf_measurements:light': 0.07537468077756511,
 'location:max_speed': 0.03403124769656329,
 'discrete:time_of_day:between12and18': 0.060086267772315176,
 'audio_naive:mfcc1:std': 0.06093427369807594,
 'audio_naive:mfcc2:std': 0.058281332172434495,
 'audio_naive:mfcc3:std': 0.041462999725892714,
 'discrete:time_of_day:between15and21': 0.043360900628226826,
 'audio_naive:mfcc4:std': 0.03704440590815199,
 'audio_naive:mfcc5:std': 0.027172904439854543,
 'audio_naive:mfcc6:std': 0.031531589822378185,
 'audio_naive:mfcc7:std': 0.027435684906716325,
 'location:min_speed': 0.02073908608430581,
 'audio_naive:mfcc8:std': 0.025375759641525303,
 'audio_naive:mfcc10:std': 0.02081059009123505,
 'audio_naive:mfcc9:std': 0.021027138241907516,
 'audio_naive:mfcc1:mean': 0.0686234276811381,
 'audio_naive:mfcc11:std': 0.02195100556164256,
 'discrete:time_of_day:between9and15': 0.037462146972628396,
 'audio_naive:mfcc12:std': 0.023618305818491604,
 'lf_measurements:screen_brightness': 0.06278706331454692,
 'watch_acceleration:3d:mean_y': 0.05426561674671741,
 'location:best_horizontal_accuracy': 0.03176257899237415,
 'proc_gyro:magnitude_spectrum:spectral_entropy': 0.044656045988136536,
 'proc_gyro:magnitude_spectrum:log_energy_band1': 0.037887218167868775,
 'discrete:time_of_day:between18and24': 0.03231772914930717}
```

13.1 Sorting and Plotting Features of Importance

[62]:
```
features_df = pd.DataFrame(features_dict, index=[0]).T.sort_values(by=0,␣
 ↪ascending=False)
features_df.plot.bar(title="Feature Importance", legend=False);
```



14 References

Major parts of this notebook were inspired from the following github guide:

Github