hr_estimation

December 5, 2024

1 Heart Rate Estimation

The goal of this exercise is to estimate the heart rate from PPG and acceleration signals using regression methods. We use data from the PPG-DaLiA dataset (https://archive.ics.uci.edu/ml/datasets/PPG-DaLiA). It includes PPG and acceleration signals as well as the reference heart rate computed from an ECG signal. These signals were collected during various activity but we focus on two of them: sitting and walking.

First, we import all the packages we will need, define some global variables, and seed the random number generators.

[18]:
```
%matplotlib widget


import copy
import itertools
import operator
import pathlib
import warnings
import IPython.display
import joblib
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_regression
from sklearn.feature_selection import SelectFromModel
from sklearn.linear_model import Lasso
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler


DATA_FILE = pathlib.Path('../data/ppg_dalia.pkl')
LOG_DIRECTORY = pathlib.Path('../logs/hr_estimation')
```

Then, we load the PPG and acceleration signals as well as the reference heart rate. The signals are already pre-processed with the following steps:

- Band-pass filtering between 0.4 and 4.0 Hz (24 - 240 bpm).
- Resampling to 25 Hz.

We also define the window length and shift length used to compute the reference heart rate.

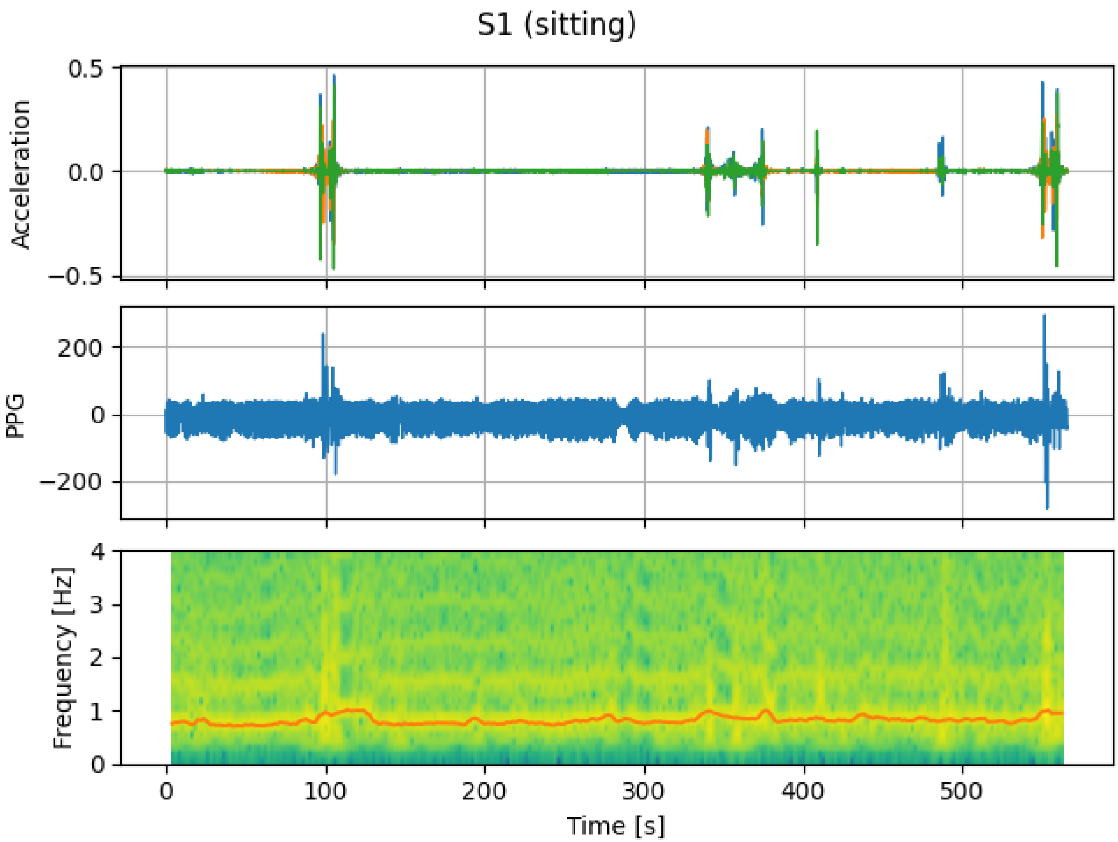
[19]:
```
FS = 25.0  # Sampling frequency of the PPG and acceleration signals in Hertz.
WINDOW_LENGTH = 8.0  # Window duration in seconds used to compute the reference␣
 ↪heart rate.
SHIFT_LENGTH = 2.0  # Shift between successive windows in seconds.

WINDOW_SIZE = round(FS * WINDOW_LENGTH)
SHIFT_SIZE = round(FS * SHIFT_LENGTH)

records = joblib.load(DATA_FILE)
subjects = set(record['subject'] for record in records)

print(f'Window length: {WINDOW_LENGTH} s (n = {WINDOW_SIZE})')
print(f'Shift length: {SHIFT_LENGTH} s (n = {SHIFT_SIZE})')
print(f'Number of records: {len(records)}')
print(f'Number of subjects: {len(subjects)}')
```

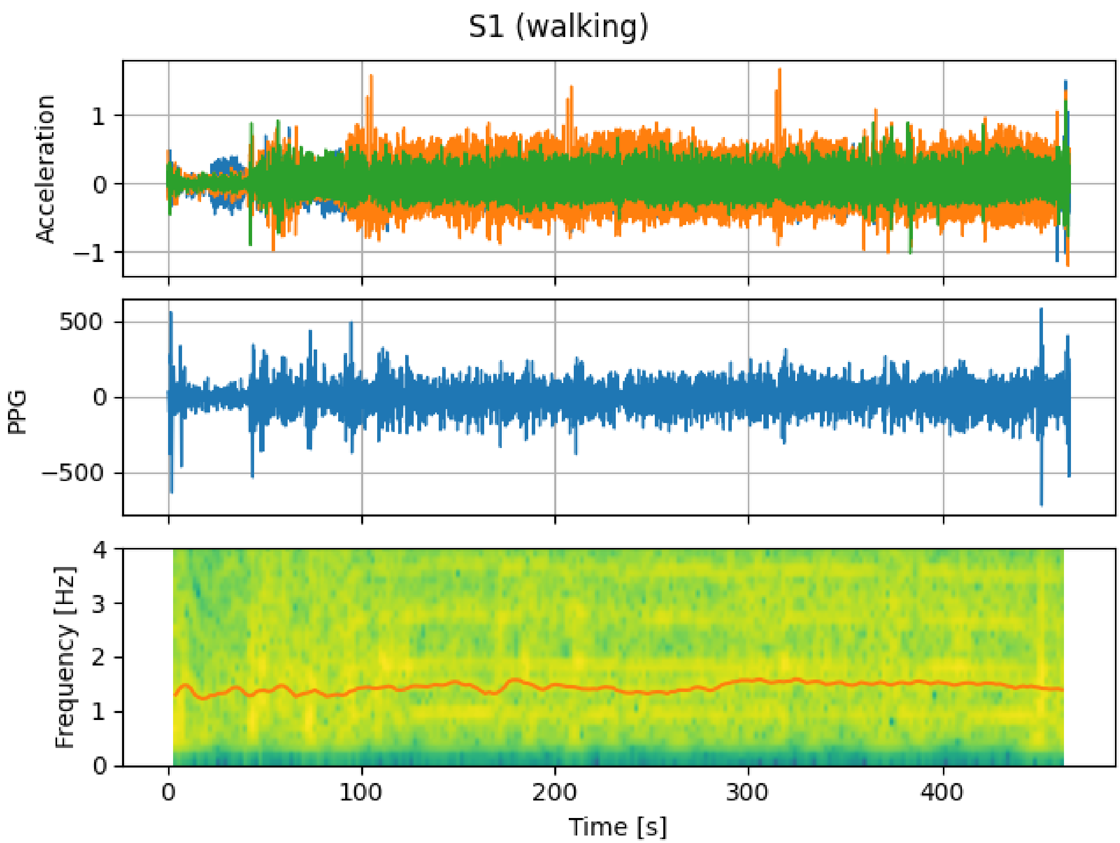
```
Window length: 8.0 s (n = 200)
Shift length: 2.0 s (n = 50)
Number of records: 29
Number of subjects: 15
```

Here are two examples of PPG and acceleration signals. One recorded when the subject is sitting and one recorded when the subject is walking.

[20]:
```
def plot_signals(record):
    signals = record['signals']
    hr = record['hr']

    fig, axes = plt.subplots(3, 1, sharex='all', constrained_layout=True)
    plt.suptitle(f'{record["subject"]} ({record["activity"]})')

    plt.sca(axes.flat[0])
    plt.plot(signals['time'].to_numpy(),
             signals[['acc_x', 'acc_y', 'acc_z']].to_numpy(),
             linewidth=1)
    plt.grid()
    plt.ylabel('Acceleration')

    plt.sca(axes.flat[1])
    plt.plot(signals['time'].to_numpy(), signals['ppg'].to_numpy(),
             linewidth=1)
    plt.grid()
```

```
    plt.ylabel('PPG')

    plt.sca(axes.flat[2])
    plt.specgram(signals['ppg'].to_numpy(), Fs=FS, NFFT=WINDOW_SIZE,
                 noverlap=WINDOW_SIZE - SHIFT_SIZE)
    plt.plot(hr['time'].to_numpy(), hr['hr'].to_numpy() / 60.0,
             color='tab:orange')
    plt.ylim(0.0, 4.0)
    plt.xlabel('Time [s]')
    plt.ylabel('Frequency [Hz]')


plot_signals(records[0])
plot_signals(records[1])
```





By zooming on the PPG signal, it is clear that walking cause a degradation in signal quality.

We will try to estimate the heart rate on sliding windows of the PPG and acceleration signals. To make things easier, we use the same window length and shift between windows as the reference heart rate.

So the next step is to extract sliding windows from all the records. We also extract the corresponding subject identifier for splitting the windows into subsets for training, validation, and testing.

In addition, we also prepare windows that include only the PPG signal (first channel).

[21]:
```
def extract_windows(record):
    x = record['signals'][['ppg', 'acc_x', 'acc_y', 'acc_z']].to_numpy()
    n = x.shape[0]

    windows = []
    for i, start in enumerate(range(0, n - WINDOW_SIZE + 1, SHIFT_SIZE)):
        end = start + WINDOW_SIZE
        windows.append(x[start:end].T)
    windows = np.stack(windows)
    targets = record['hr']['hr'].to_numpy()
```

```
    return windows, targets


def extract_all_windows(records):
    windows = []
    targets = []
    subjects = []
    activities = []
    for record in records:
        x, y = extract_windows(record)
        windows.append(x)
        targets.append(y)
        subjects.extend(itertools.repeat(record['subject'], x.shape[0]))
        activities.extend(itertools.repeat(record['activity'], x.shape[0]))

    windows = np.concatenate(windows, axis=0)
    targets = np.concatenate(targets)[:, None]
    subjects = np.array(subjects)
    activities = np.array(activities)

    return windows, targets, subjects, activities


ppg_acc_windows, targets, subjects, activities = extract_all_windows(records)
ppg_windows = ppg_acc_windows[:, 0, :]

print(f'Shape of PPG and accleration windows: {ppg_acc_windows.shape}')
print(f'Shape of PPG windows: {ppg_windows.shape}')
```

```
Shape of PPG and accleration windows: (7420, 4, 200)
Shape of PPG windows: (7420, 200)
```

We have 7420 windows with 1 or 4 channels and that each window includes 200 samples (8 seconds at 25 Hz).

Next, we split the windows for training, validation, and testing by subjects. The test set includes 9 subjects, the validation set 3 subjects, and the test set 3 subjects.

[22]:
```
def split_subjects(subjects):
    val_subjects = ('S10', 'S11', 'S12')
    test_subjects = ('S13', 'S14', 'S15')

    i_val = np.flatnonzero(np.isin(subjects, val_subjects))
    i_test = np.flatnonzero(np.isin(subjects, test_subjects))
    i_train = np.setdiff1d(np.arange(subjects.size), np.union1d(i_val, i_test))

    assert not (set(subjects[i_train]) & set(subjects[i_val]))
    assert not (set(subjects[i_train]) & set(subjects[i_test]))
```

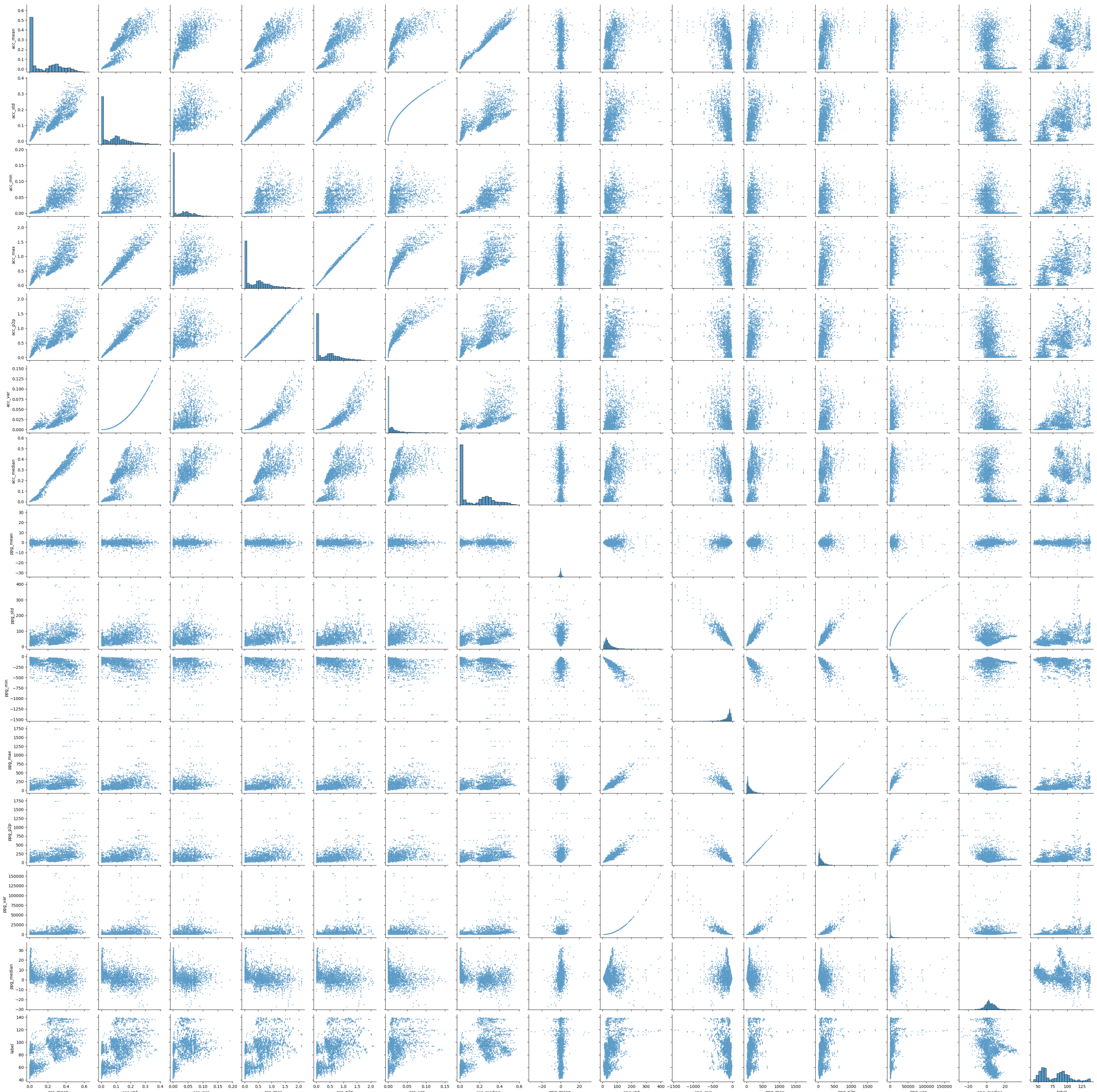
```
    assert not (set(subjects[i_val]) & set(subjects[i_test]))
    assert (set(subjects[i_train]) | set(subjects[i_val]) |␣
↪set(subjects[i_test])) == set(subjects)

    return i_train, i_val, i_test


i_train, i_val, i_test = split_subjects(subjects)

print(f'Subject used for training   : {pd.unique(subjects[i_train])}')
print(f'Subject used for validation : {pd.unique(subjects[i_val])}')
print(f'Subject used for testing    : {pd.unique(subjects[i_test])}')
```

```
Subject used for training   : ['S1' 'S2' 'S3' 'S4' 'S5' 'S6' 'S7' 'S8' 'S9']
Subject used for validation : ['S10' 'S11' 'S12']
Subject used for testing    : ['S13' 'S14' 'S15']
```

Now we extract features from the windows.

[23]:
```
acc_norm = np.zeros([ppg_acc_windows.shape[0], ppg_acc_windows.shape[2]])
for instance in range(ppg_acc_windows.shape[0]):
    ppg_acc = ppg_acc_windows[instance, 1:, :]
    acc_norm[instance, :] = np.sqrt(np.sum(np.power(ppg_acc, 2), axis=0))


features = pd.DataFrame({
    'acc_mean': np.mean(acc_norm, axis=1),
    'acc_std': np.std(acc_norm, axis=1),
    'acc_min': np.min(acc_norm, axis=1),
    'acc_max': np.max(acc_norm, axis=1),
    'acc_p2p': np.max(acc_norm, axis=1) - np.min(acc_norm, axis=1),
    'acc_var': np.power(np.std(acc_norm, axis=1), 2),
    'acc_median': np.median(acc_norm, axis=1),
    'ppg_mean': np.mean(ppg_windows, axis=1),
    'ppg_std': np.std(ppg_windows, axis=1),
    'ppg_min': np.min(ppg_windows, axis=1),
    'ppg_max': np.max(ppg_windows, axis=1),
    'ppg_p2p': np.max(ppg_windows, axis=1) - np.min(acc_norm, axis=1),
    'ppg_var': np.power(np.std(ppg_windows, axis=1), 2),
    'ppg_median': np.median(ppg_windows, axis=1),
})


def plot_features(f, y):
    data = f.copy()
    data['label'] = y.ravel()
    sns.pairplot(data, plot_kws={'s': 4})
```

```
plot_features(features.iloc[i_train], targets[i_train])
```



It is also possible to select the most relevant features using various methods. Here, we define implement three fature selection techniques: lasso, univariate, hybrid.

[24]:
```
class FeatureSelector:

    def __init__(self, method, numbers):
        self.method = method.lower()
        self.numbers = numbers

    def apply(self, features, targets):
```

```
        features_names = [column for column in features.columns
                          if column not in ['reference']]
        features_selection = features.copy()
        features_selection.insert(0, 'reference', targets)
        features_selection = features_selection.dropna(axis=0, how='any', inplace=False)
        ranks = self.rank_features(features_selection[features_names],
                                   features_selection['reference'],
                                   self.method)
        del features_selection
        return self.select_features(ranks, self.numbers)

    @staticmethod
    def select_features(ranks, feature_num):
        ranks.sort_values(by='ranks', axis=0, ascending=False, inplace=True,
                          kind='quicksort', ignore_index=True)
        return ranks['feature_names'].iloc[: feature_num].tolist()

    @staticmethod
    def rank_features(features, reference, method):
        def univariate_selection(data, ref):
            selector = SelectKBest(f_regression, k="all")
            scores = selector.fit(data, ref).scores_
            return scores / np.nansum(scores)

        def lasso_selection(data, ref):
            alphas = np.arange(0.01, 0.3, 0.01)
            coefficients = np.empty([len(alphas), data.shape[1]])
            for row, alpha in enumerate(alphas):
                selector = SelectFromModel(Lasso(alpha=alpha), prefit=False)
                coefficients[row, :] = selector.fit(data, ref).estimator_.coef_
            coefficients = np.abs(coefficients)
            real_ranks = np.nansum(coefficients, axis=0)
            return real_ranks / np.nansum(real_ranks)

        if method == 'lasso':
            ranks = lasso_selection(features, reference)
        elif method == 'univariate':
            ranks = univariate_selection(features, reference)
        elif method == 'hybrid':
            rank_lasso = lasso_selection(features, reference)
            rank_univariate = univariate_selection(features, reference)
            rank_combined = rank_lasso + rank_univariate
            ranks = rank_combined / np.nansum(rank_combined)
        else:
            raise TypeError("Feature selection method is not supported")
        return pd.DataFrame({
```

```
            'feature_names': features.columns,
            'ranks': ranks,
        })

feature_selection_method = 'univariate'
feature_selection_numbers = 4
features_list = FeatureSelector(feature_selection_method,␣
 ↪feature_selection_numbers).apply(features.iloc[i_val], targets[i_val])
print(f"Selected features:{features_list}")
```

```
Selected features:['acc_mean', 'acc_median', 'acc_std', 'acc_min']
```

Now we define the regression models: linear regression, support vector regression.

[25]:
```
class ModelBuilder:

    def __init__(self, config):
        self.config = config['model']

    def apply(self):
        return eval(f"self._build_{self.config['name']}()")

    def _build_lregression(self):
        return make_pipeline(
            StandardScaler(),
            LinearRegression())

    def _build_svr(self, kernel='rbf', gamma='scale', regularization=1):
        if 'kernel' in self.config.keys():
            kernel = self.config['kernel']
        if 'gamma' in self.config.keys():
            gamma = self.config['gamma']
        if 'regularization' in self.config.keys():
            regularization = self.config['regularization']
        return make_pipeline(
            StandardScaler(),
            SVR(kernel=kernel, gamma=gamma, C=regularization))
```

Now, we define a class for the training of the models.

[26]:
```
class ModelTrainer:

    def __init__(self, config):
        self.config = config['feature']

    def apply(self, model, features, reference, i_train):
        features_list = self._get_features_list(list(features.columns))
        features_train = features.copy()
```

```
        features_train.insert(0, 'reference', reference)
        features_train = features_train.iloc[i_train].copy()

        features_train = features_train.dropna(axis=0, how='any', inplace=False,
                                               subset=features_list +␣
↪['reference'])
        return model.fit(
            features_train[features_list].values, features_train['reference'].
↪values)

    def _get_features_list(self, current_features):
        if 'all' in self.config['list']:
            features_list = [feature for feature in current_features
                             if feature not in self.config['exclusion'] +␣
↪['reference']]
        else:
            features_list = [feature for feature in
                             self.config['list']
                             if feature in current_features and feature not
                             in self.config['exclusion'] + ['reference']]
        return features_list
```

We also define a class to apply the trained models on the test data.

[27]:
```
class ModelTester:

    def __init__(self, config):
        self.config = config['feature']

    def apply(self, model, features):
        features_list = self._get_features_list(list(features.columns))
        inx = np.logical_not(
            np.sum(np.isnan(features[features_list]), 1).astype(bool))
        detections = np.zeros_like(inx, dtype=float)
        detections[:] = np.nan
        detections[inx] = model.predict(features[features_list].values[inx])
        return pd.DataFrame({
            'prediction': detections,
        })

    def _get_features_list(self, current_features):
        if 'all' in self.config['list']:
            features_list = [feature for feature in current_features
                             if feature not in self.config['exclusion'] +␣
↪['reference']]
        else:
            features_list = [feature for feature in
```

```
                                self.config['list']
                                if feature in current_features and feature not
                                in self.config['exclusion'] + ['reference']]
        return features_list
```

Inorder to evaluate the results of the models, we define an Evaluator class as follows:

[28]:
```
class Evaluator:

    def __init__(self):
        pass

    def apply(self, result, reference, i_train, i_test):
        metrics = []
        for subset, indices in (('train', i_train), ('test', i_test)):
            metrics.append({
                'subset': subset,
                **self.compute_performance_parameters(result[indices],␣
↪reference[indices]),
            })
        return pd.DataFrame(metrics)

    @staticmethod
    def compute_performance_parameters(result, reference):
        error = np.zeros_like(reference)
        error[:] = np.nan
        inx = reference != 0
        error[inx] = 100 * ((reference[inx] - result[inx]) / reference[inx])
        error = error[error != np.nan]
        return {
            'mean': np.mean(error),
            'std': np.std(error),
            'rmse': np.sqrt(np.mean(np.power(error, 2))),
        }
```

The final step before training and evaluating the models is to define the configurations of the different models.

We will train the models with the following configurations:

- Linear without features selection
  - Using all the features
- Linear regression with features selection
  - Using the selected features
- SVR with features selection
  - Using the selected features
  - kernel: rbf
  - gamma:scale
  - regularization: 1

[29]:

```
exclude_features = []
configs = {
    'linear_regression_all_features': {
        'feature': {
            'list': 'all',
            'exclusion': exclude_features,
            'selection_method': [],
            'selection_numbers': np.nan,
        },
        'model': {
            'name': 'lregression',
        },
    },
    'linear_regression_selected_features': {
        'feature': {
            'list': features_list,
            'exclusion': exclude_features,
            'selection_method': feature_selection_method,
            'selection_numbers': feature_selection_numbers,
        },
        'model': {
            'name': 'lregression',
        },
    },
    'svr_all_features': {
        'feature': {
            'list': 'all',
            'exclusion': exclude_features,
            'selection_method': [],
            'selection_numbers': np.nan,
        },
        'model': {
            'name': 'svr',
            'kernel': 'rbf',
            'gamma': 'scale',
            'regularization': 1,
        },
    },
    'svr_selected_features': {
        'feature': {
            'list': features_list,
            'exclusion': exclude_features,
            'selection_method': feature_selection_method,
            'selection_numbers': feature_selection_numbers,
        },
        'model': {
            'name': 'svr',
```

```
            'kernel': 'rbf',
            'gamma': 'scale',
            'regularization': 1,
        },
    },
}
```

Now, we are ready to train the models.

[30]:
```
models = {}
for name, config in configs.items():
    print(f' * Training {name!r} model')
    model = ModelBuilder(config).apply()
    models[name] = ModelTrainer(config).apply(model, features, targets, i_train)
```

```
 * Training 'linear_regression_all_features' model
 * Training 'linear_regression_selected_features' model
 * Training 'svr_all_features' model
 * Training 'svr_selected_features' model
```

Here, we evaluate the trained models on the features.

[31]:
```
output = {}
for name, config in configs.items():
    print(f' * Applying {name!r} model')
    output[name] = ModelTester(config).apply(models[name], features)
```

```
 * Applying 'linear_regression_all_features' model
 * Applying 'linear_regression_selected_features' model
 * Applying 'svr_all_features' model
 * Applying 'svr_selected_features' model
```

Now that all models are trained we can evaluate them on the subsets for training, validation, and testing.

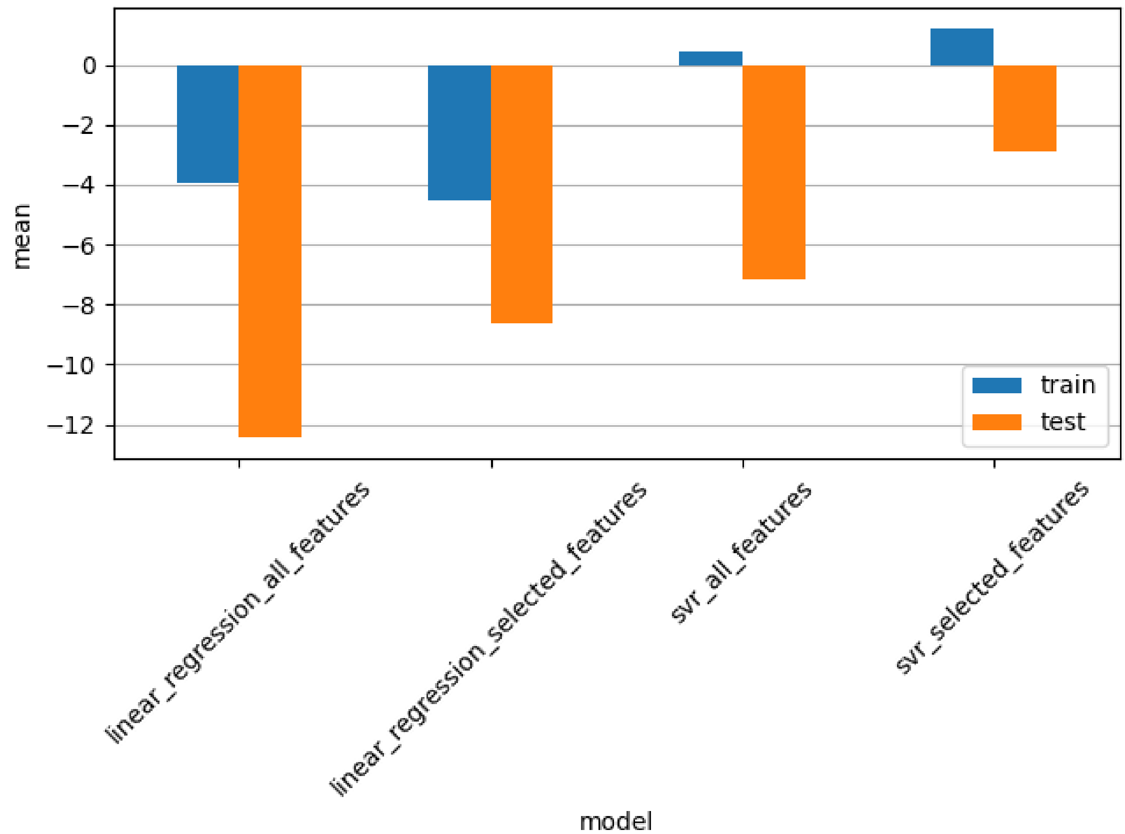
[32]:
```
metrics = []
for name, config in configs.items():
    print(f'Evaluating {name!r} model')
    performance = Evaluator().apply(output[name]['prediction'].values, targets[:
 ↪, 0], i_train, i_test)
    performance.insert(0, 'model', name)
    metrics.append(performance)
print("\n*** Performance report ***\n")
metrics = pd.concat(metrics, axis=0, ignore_index=True)
metrics = metrics.set_index(['model', 'subset'])
index = metrics.index.get_level_values(0).unique()
columns = pd.MultiIndex.from_product([metrics.columns, metrics.index.
 ↪get_level_values(1).unique()])
metrics = metrics.unstack().reindex(index=index, columns=columns)
```

```
IPython.display.display(metrics)
```

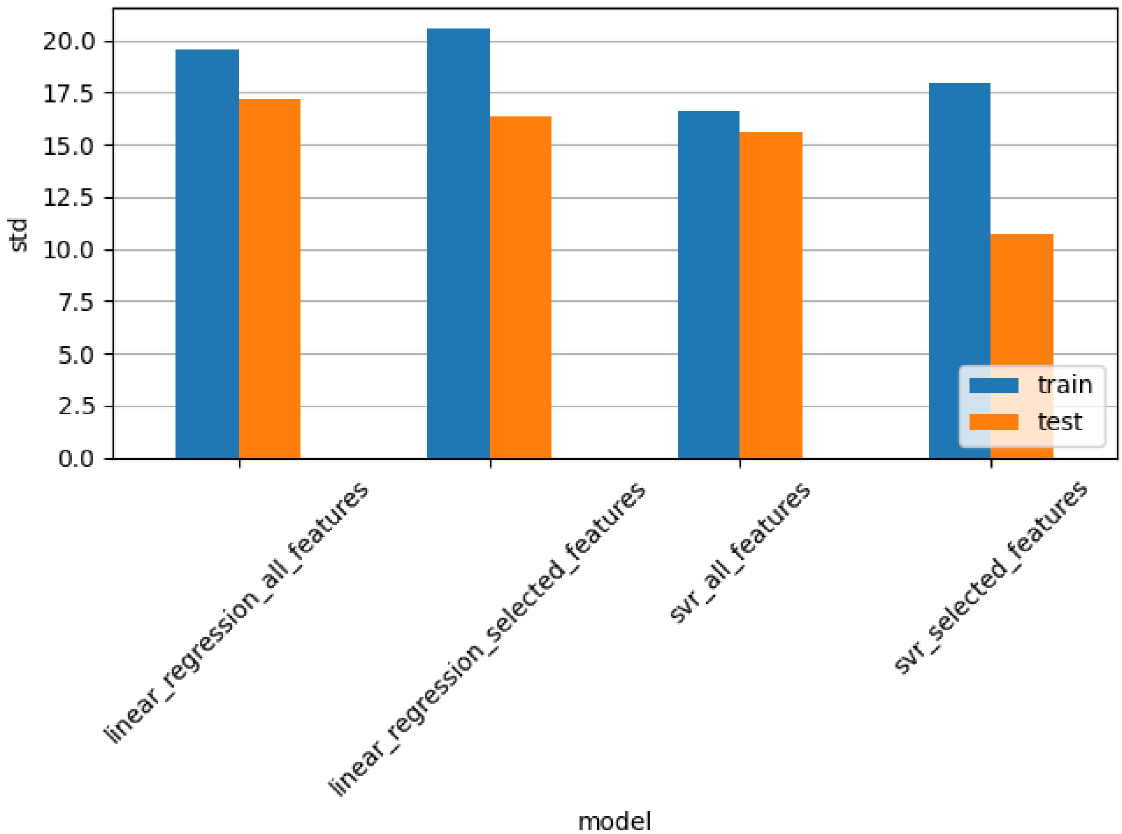
```
Evaluating 'linear_regression_all_features' model
Evaluating 'linear_regression_selected_features' model
Evaluating 'svr_all_features' model
Evaluating 'svr_selected_features' model

*** Performance report ***


                                          mean                  std  \
subset                                   train       test     train
model
linear_regression_all_features       -3.924053 -12.435107  19.565851
linear_regression_selected_features -4.549709  -8.650772  20.517729
svr_all_features                      0.418621  -7.181589  16.625634
svr_selected_features                 1.217230  -2.908962  17.959907


                                                     rmse
subset                                    test      train       test
model
linear_regression_all_features       17.199001  19.955468  21.223514
linear_regression_selected_features  16.334608  21.016114  18.483919
svr_all_features                     15.572246  16.630904  17.148471
svr_selected_features                10.697804  18.001109  11.086256
```

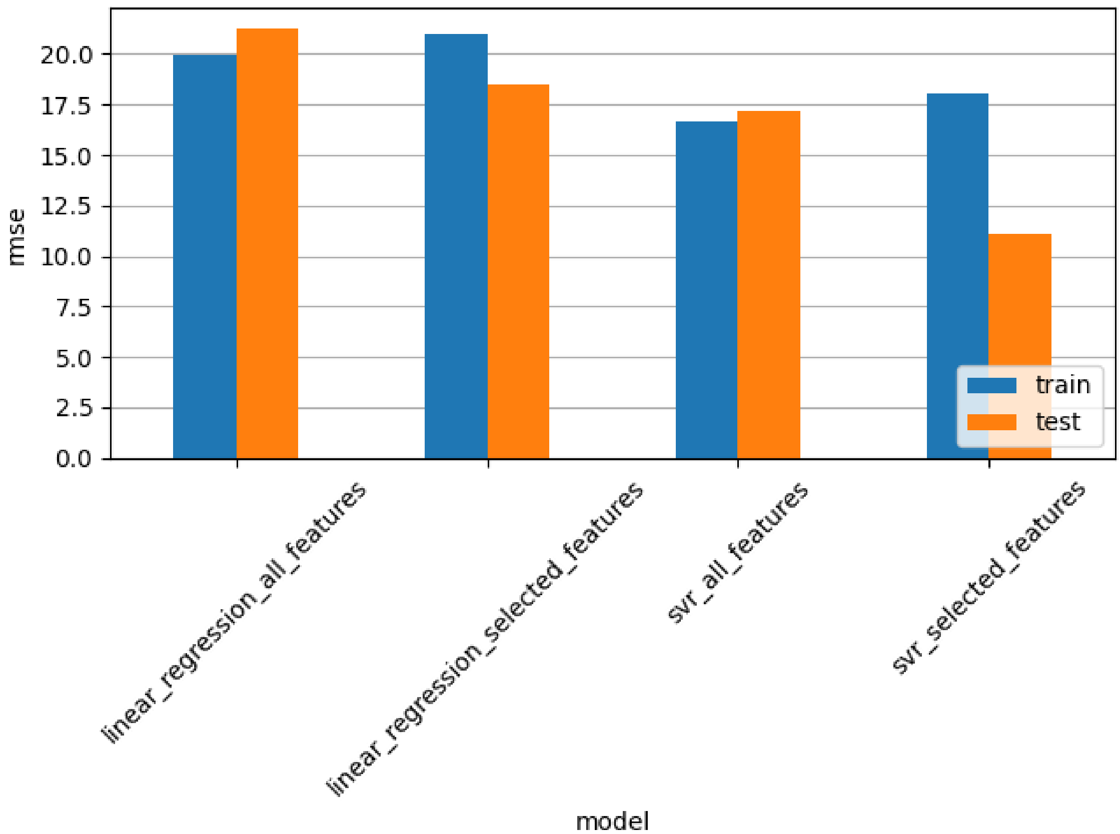
We can also plot the different metrics.

[33]:
```
def plot_metrics(data):
    for metric in data.columns.get_level_values(0).unique():
        if metric == 'count':
            continue
        df = data[metric]
        plt.figure(constrained_layout=True)
        plt.gca().set_axisbelow(True)
        df.plot(kind='bar', ylabel=metric, ax=plt.gca())
        plt.grid(axis='y')
        plt.legend(loc='lower right')
        plt.gca().xaxis.set_tick_params(rotation=45)


plot_metrics(metrics)
```



mean
0
−2
−4
−6
−8
−10
−12
train
test
linear_regression_all_features
linear_regression_selected_features
svr_all_features
svr_selected_features
model


20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
std
train
test
linear_regression_all_features
linear_regression_selected_features
svr_all_features
svr_selected_features
model



2 Exercise Questions

2.1 Question 1

If you want to select a set of features manually, which features would you choose and why?

Answer

Generally, one would choose the features that are the most important to explain all the different data available. For example, if one notices a strong correlation between the change of the value of one feature and the output, it is optimal to select such a feature.

Another important fact to take into account is the independancy of the features : if one feature is strongly correlated with another, there is no use in keeping both features in the model, since one of them is enough to illustrate the behaviour of the other.

Taking these facts into account, one can see that the labels are not very much correlated with the PPG information (the last column/last row plots in Figure 3 all have a low correlation). On the other hand, the accelerometer data are much more correlated; taking into account the fact that the correlation between features should be kept at its lowest, a good feature choice - if we had to take three of them - would be acc_var, acc_mean and acc_min for example.

2.2 Question 2

Do the automatically selected features match your manually selected features? Explain the reasons for any similarities and/or differences.

Answer

The automatically selected features are similar to our choice : acc_var is directly proportionnal to the square of acc_std, therefore both are related.

The reason why the features match is because the automatically selected features are chosen using SelectKBest, which uses the ANOVA F-value to extract the score of each feature, and this is based on the criteria we wrote down in Question 1. Our manual choice was probably less precise since it was only based on the graphs, but it does not change much in the end, since the features are meaningful and easily understandable by humans.

2.3 Question 3

Do you think that the feature selection was useful in this exercise? Why?

Answer

Looking at Figures 4, 5 and 6, the mean error, standard deviation error RMSE of the test data all decrease for the test data when using only selected features, showing an overall better performance of the model, while the model and computational complexity were successfully reduced.

2.4 Question 4

How do you interpret mean, std, and rmse errors of the models?

Answer

The mean error can be interpreted as the following: the average "signed-distance" from which our predictions are to their real values.

The standard deviation error can be considered as the variability of the prediction to the real values. Predicted values are different to the real values, however, if we take a 2D plane, the predictions can tend to always be different by 2 on the y-axis and -1 on the x-axis. The lower the STD, the more similar the errors between predictions are

The Root Mean Squared Error is the average "squared-distance" from which our predictions are to their real values, it indicates the overall performance of the model.

2.5 Question 5

Considering all conditions, which model will you finally choose to estimate heart rate? Why?

Answer

To choose the best model, we would ideally take the model presenting the smallest metrics for absolute, std and rmse. In all three metrics, the linear regression models express higher values. Which is why we choose one of the SVR models. SVR using only the selected features, although the train error metrics are slightly higher than with all features, it seems to give the best test results when considering the test error metrics, and it also reduces the computational costs compared to the SVR using all the features.