

linear_regression_XYZ_MET-cycling-light-new

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```
[1]: from helpers import pandas_helper as pdh
from helpers import math_helper as mth
from sensors.activpal import *
from utils import read_functions

from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import RFE
from sklearn.model_selection import train_test_split, KFold, cross_val_score
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

from math import sqrt
from numpy import mean, absolute

import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import datetime

activpal = Activpal()

activity_focus = 'fietsen licht'
respondents = ['BMR002', 'BMR004', 'BMR011', 'BMR012', 'BMR014', 'BMR018',
↳ 'BMR031', 'BMR032', 'BMR033', 'BMR034', 'BMR036', 'BMR041', 'BMR042',
↳ 'BMR043', 'BMR044', 'BMR052', 'BMR053', 'BMR055', 'BMR058', 'BMR064',
↳ 'BMR097', 'BMR098']
test_respondents = ['BMR008', 'BMR040', 'BMR030']
```

1 Defining functions

1.0.1 Method to retrieve DataFrame containing all information for regression

```
[2]: def get_regression_df(respondent, activity):
    start, stop = get_timestamps(respondent, activity)
    res_number = get_respondent_number(respondent)
```

```

# read in all dataframes necessary
respondents_df = pdh.read_csv_respondents_cleaned()
vyntus_df, min_index, max_index = get_vyntus_df(respondent, respondents_df.
↳loc[res_number, 'weight_kg'], start, stop)
activpal20_df = get_activpal20_df(respondent, min_index, max_index)

# add met, mag acc, and mean speed to new dataframe
new_df = pd.DataFrame(index=activpal20_df.index)
new_df['mean_met'] = vyntus_df['met']

new_df['sum_mag_acc'] = activpal20_df['sum_mag_acc']
new_df['mean_mag_acc'] = activpal20_df['mean_mag_acc']
new_df['std_mag_acc'] = activpal20_df['std_mag_acc']
new_df['var_mag_acc'] = activpal20_df['var_mag_acc']

new_df['sum_speed'] = activpal20_df['sum_speed']
new_df['mean_speed'] = activpal20_df['mean_speed']
new_df['std_speed'] = activpal20_df['std_speed']
new_df['var_speed'] = activpal20_df['var_speed']

# add features to new dataframe
new_df['estimated_level'] = respondents_df.loc[res_number,
↳'estimated_level']
new_df['length_cm'] = respondents_df.loc[res_number, 'length_cm']
new_df['weight_kg'] = respondents_df.loc[res_number, 'weight_kg']
new_df['waist_circumference'] = respondents_df.loc[res_number,
↳'waist_circumference']
new_df['gender'] = respondents_df.loc[res_number, 'gender']
new_df['age_category'] = respondents_df.loc[res_number, 'age_category']

return new_df

def get_regression_dfs(respondents, activity):
    all_df = pd.DataFrame(index=pd.to_datetime([]))

    for cor in respondents:
        df = get_regression_df(cor, activity)
        all_df = pd.concat([all_df, df])

    all_df.sort_index(inplace=True)
    return all_df

```

1.0.2 Helper method, returning start and stop timestamps for an activity

```
[3]: def get_timestamps(respondent, activity):
    activities_df = read_functions.read_activities(respondent)
    start = activities_df.loc[activity].start
    stop = activities_df.loc[activity].stop

    return (start, stop)
```

1.0.3 Helper method, returning the number of respondent code

```
[4]: def get_respondent_number(respondent):
    if ('BMRO' in respondent):
        return int(respondent.replace('BMRO', ''))

    if ('BMR' in respondent):
        return int(respondent.replace('BMR', ''))
```

1.0.4 Helper method, returning Vyntus (lab data)

The DataFrame contains MET and other information necessary for regression

The DataFrame is resampled to minutes by mean

```
[5]: def get_vyntus_df(respondent, weight, start, stop):
    vyntus_df = pdh.read_csv_vyntus(respondent)
    mask = (vyntus_df.index >= start) & (vyntus_df.index < stop)
    vyntus_df = vyntus_df.loc[mask]

    min_index = vyntus_df.index.min()
    max_index = vyntus_df.index.max()

    vyntus_df['vyn_V02'] = [float(vo2.replace(',', '.')) if type(vo2) == str
    ↪ else vo2 for vo2 in vyntus_df['vyn_V02']]
    vyntus_df['met'] = mth.calculate_met(vyntus_df['vyn_V02'], weight)

    vyntus_df = vyntus_df.resample('60s').mean()[:-1]

    return (vyntus_df, min_index, max_index)
```

1.0.5 Helper method, returning Activpal20

The DataFrame contains summation of magnitude of acceleration

The DataFrame is resampled to minutes by summation

```
[6]: def get_activpal20_df(respondent, start, stop):
    df = activpal.read_data(respondent, start, stop)

    mask = (df.index >= start) & (df.index < stop)
    df = df.loc[mask]
    df = df[['pal_accX', 'pal_accY', 'pal_accZ']].apply(mth.convert_value_to_g)

    mag_acc = mth.to_mag_acceleration(df['pal_accX'], df['pal_accY'],
    ↪df['pal_accZ'])
    speed = get_speed(df['pal_accX'], df['pal_accY'], df['pal_accZ'])

    df['sum_mag_acc'] = mag_acc
    df['mean_mag_acc'] = mag_acc
    df['std_mag_acc'] = mag_acc
    df['var_mag_acc'] = mag_acc

    df['sum_speed'] = speed
    df['mean_speed'] = speed
    df['std_speed'] = speed
    df['var_speed'] = speed

    agg_dict = {
        'sum_mag_acc': 'sum', 'mean_mag_acc': 'mean', 'std_mag_acc': 'std',
    ↪ 'var_mag_acc': 'var',
        'sum_speed': 'sum', 'mean_speed': 'mean', 'std_speed': 'std',
    ↪ 'var_speed': 'var'
    }

    df = df.resample('60s').agg(agg_dict)[-1]

    return df
```

1.0.6 Helper method, returns speed

```
[7]: def get_speed(x_acc, y_acc, z_acc):
    activpal_time = 0.05

    x_vel = x_acc.diff()**2
    y_vel = y_acc.diff()**2
    z_vel = z_acc.diff()**2

    return (x_vel + y_vel + z_vel) / activpal_time
```

1.0.7 Helper method to plot prediction results

```
[8]: def plot_results_bar(pred_y, valid_y):
    plt.figure(figsize=(10,5))
    bar_width = 0.35

    pred_index = np.arange(len(pred_y))
    y_index = np.arange(len(valid_y)) + bar_width
    plt.bar(pred_index, pred_y, bar_width, color='blue', label='Prediction')
    plt.bar(y_index, valid_y, bar_width, color='red', label='Ground Truth')

    plt.xlabel('# Minute')
    plt.ylabel("MET")
    plt.title('MET predictions on validation per minute')
    plt.xticks(pred_index + 0.15, pred_index)
    plt.legend(loc='best')
    plt.grid()
    plt.show()
```

2 Data

Load the data and check for null values, in this case there are no null values

```
[27]: data = get_regression_dfs(respondents, activity_focus)
data.isnull().sum()
```

```
[27]: mean_met          0
sum_mag_acc          0
mean_mag_acc         0
std_mag_acc          0
var_mag_acc          0
sum_speed            0
mean_speed           0
std_speed            0
var_speed            0
estimated_level      0
length_cm            0
weight_kg            0
waist_circumference  0
gender              0
age_category         0
dtype: int64
```

Split the dataset into training and validation (80/20)

```
[28]: all_features = data.columns.drop('mean_met')
train_X, valid_X, train_y, valid_y = train_test_split(data[all_features],
↳data['mean_met'], test_size=0.2, random_state=0)
```

```
[29]: data_test = get_regression_dfs(test_respondents, activity_focus)
data_test.isnull().sum()
```

```
[29]: mean_met          0
sum_mag_acc          0
mean_mag_acc         0
std_mag_acc          0
var_mag_acc          0
sum_speed            0
mean_speed           0
std_speed            0
var_speed            0
estimated_level      0
length_cm            0
weight_kg            0
waist_circumference  0
gender              0
age_category         0
dtype: int64
```

Split the test dataset into test X and Y

```
[30]: test_X = data_test.drop('mean_met', axis=1)
test_y = data_test.mean_met
```

2.0.1 Scaling

Because this notebook is working with a Linear Regression model and the feature values differ greatly, we scale the data to prevent non-convergence and oscillation

```
[31]: scaler = StandardScaler()
scaler.fit(train_X)
train_X = scaler.transform(train_X)
valid_X = scaler.transform(valid_X)
data_X = scaler.transform(data[all_features])
test_X = scaler.transform(test_X)
```

2.0.2 RFE

Use RFE iteratively on training and validation set to find the optimal minimum number of features and the features themselves for the model

```

[32]: r2t = []
      r2v = []

      features_support = None

      for i in range(1, train_X.shape[1]):
          model = LinearRegression()
          rfe = RFE(model, n_features_to_select=i)

          rfe.fit(train_X, train_y)
          model.fit(rfe.transform(train_X), train_y)

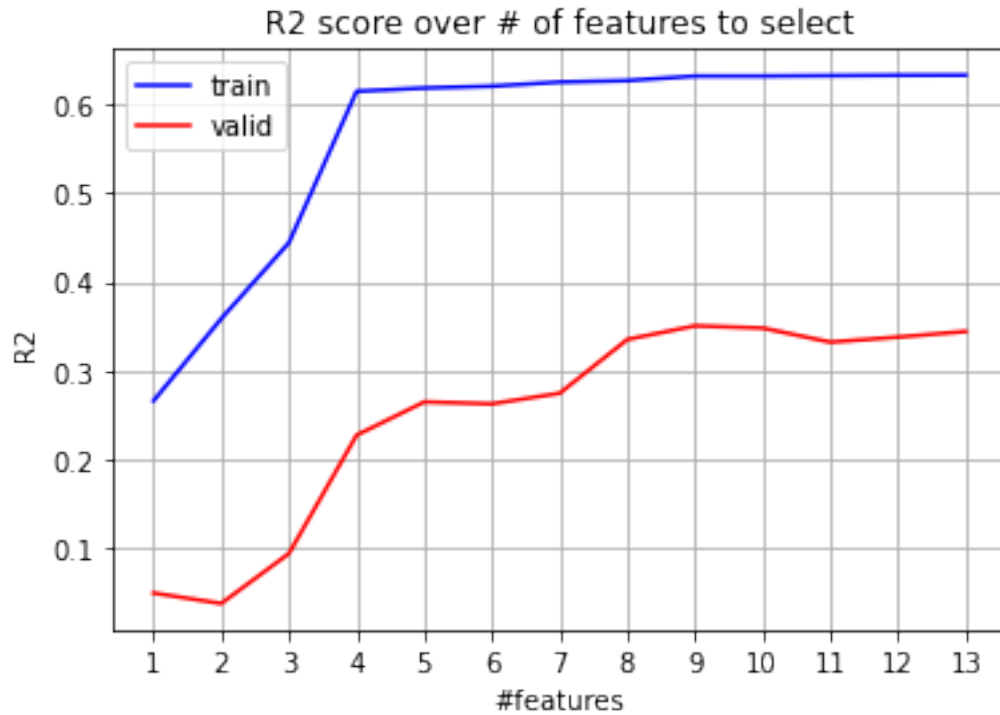
          r2t.append(model.score(rfe.transform(train_X), train_y))
          r2v.append(model.score(rfe.transform(valid_X), valid_y))

          # if optimal number of features reached, save the best features
          if i == 8:
              features_support = rfe.support_

      plt.title('R2 score over # of features to select')
      plt.plot(range(1, train_X.shape[1]), r2t, c='b', label='train')
      plt.plot(range(1, valid_X.shape[1]), r2v, c='r', label='valid')
      plt.xlabel('#features')
      plt.xticks(range(1, len(train_X[0])))
      plt.ylabel('R2');
      plt.grid()
      plt.legend(loc='best')
      plt.show()

      print(all_features[features_support])

```



```
Index(['sum_mag_acc', 'std_mag_acc', 'var_mag_acc', 'sum_speed', 'std_speed',
      'var_speed', 'weight_kg', 'waist_circumference'],
      dtype='object')
```

Here we can see that the minimum optimal number of features is 8

Remove all columns except best features

```
[33]: train_X = np.delete(train_X, features_support, axis=1)
      valid_X = np.delete(valid_X, features_support, axis=1)
      data_X = np.delete(data_X, features_support, axis=1)
      test_X = np.delete(test_X, features_support, axis=1)
```

3 Model

```
[34]: model = LinearRegression()
```


4 Training

```
[35]: model.fit(train_X, train_y)
```

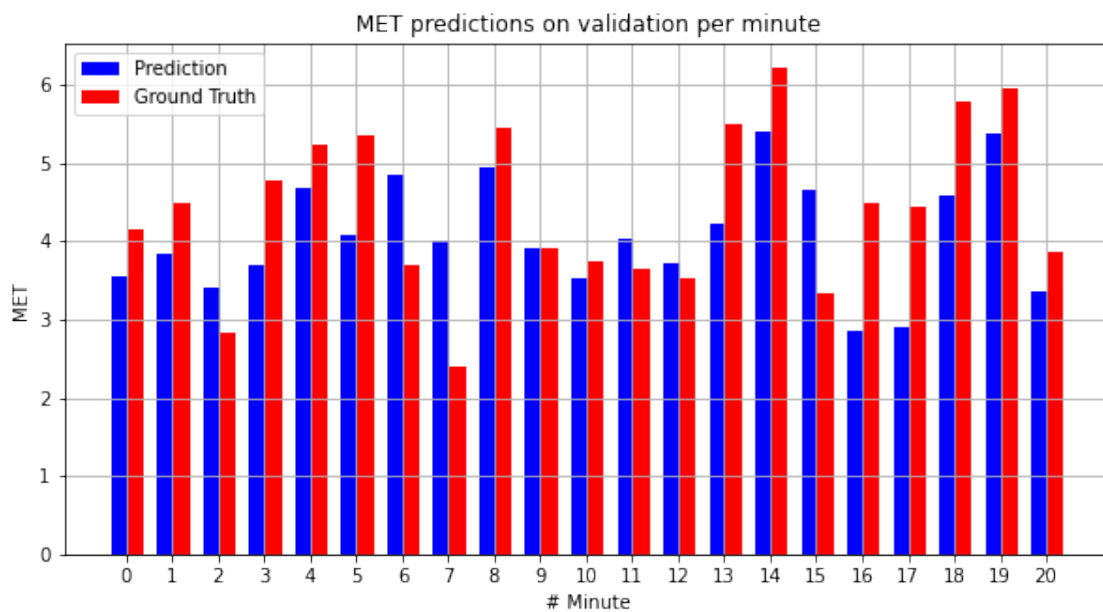
```
[35]: LinearRegression()
```

5 Evaluation

5.0.1 Results Validation Set

```
[36]: pred_y = model.predict(valid_X)

plot_results_bar(pred_y, valid_y)
print('MSE: %.2f' % mean_squared_error(valid_y, pred_y))
print('R2: %.2f' % r2_score(valid_y, pred_y))
```



MSE: 0.93

R2: 0.11

5.0.2 Results 5-fold Cross Validation

```
[37]: model2 = LinearRegression()

mse = cross_val_score(model2, data_X, data.mean_met,
    ↪scoring='neg_mean_squared_error')
r2 = cross_val_score(model2, data_X, data.mean_met, scoring='r2')

print('Mean MSE: %.2f +/- %.2f' % (mse.mean(), mse.std()))
print('Mean R2: %.2f +/- %.2f' % (r2.mean(), r2.std()))
```

Mean MSE: -1.30 +/- 0.47

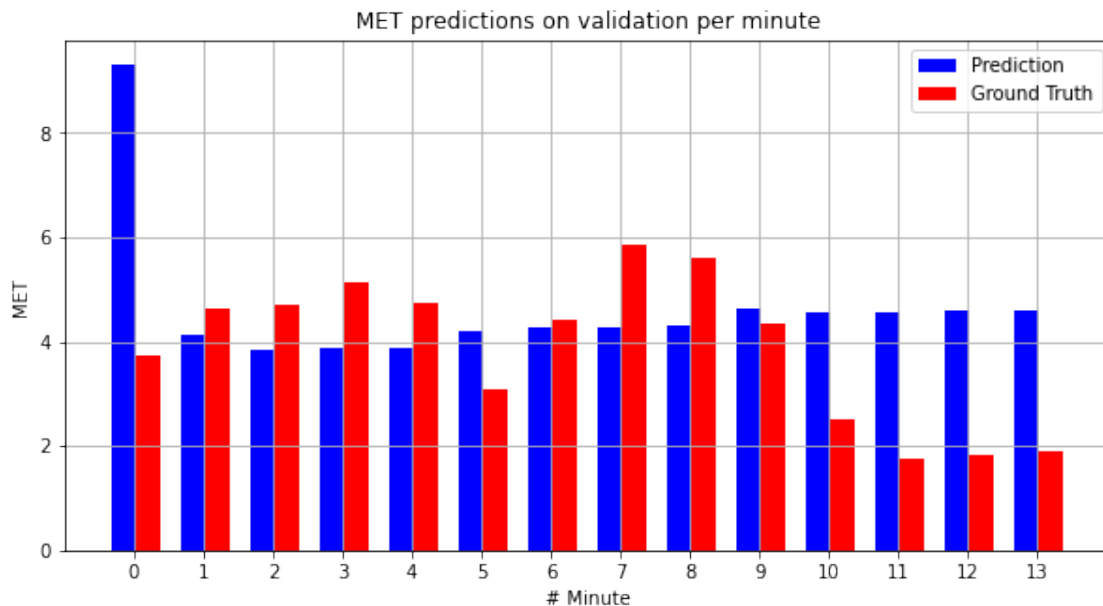
Mean R2: 0.11 +/- 0.16

5.0.3 Results test set

```
[38]: test_pred_y = model.predict(test_X)

plot_results_bar(test_pred_y, test_y)

print('MSE: %.2f' % mean_squared_error(test_y, test_pred_y))
print('R2: %.2f' % r2_score(test_y, test_pred_y))
```



MSE: 4.79

R2: -1.57

6 Conclusion

The Linear Regression model does not score well and is probably underfitting because the model is too simplistic for this dataset.

[]: