Polar

October 2, 2020

1 Imports

[1]:
```
import json
from functools import reduce
from os import listdir
from os.path import isfile, join
from pathlib import Path

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import statsmodels.api as sm
import statsmodels.formula.api as smf
import tabulate
from pylab import rcParams
from scipy.stats import shapiro
from statsmodels.graphics.gofplots import qqplot
from statsmodels.stats.diagnostic import het_goldfeldquandt
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

[2]:
```
from IPython.display import display, HTML
```

2 Setup

[3]:
```
# Set figure size
rcParams['figure.figsize'] = (4, 4)

# Folder for images
Path('img').mkdir(parents=True, exist_ok=True)

# Nice float format
pd.options.display.float_format = "{:,.2f}".format
```

3 Data description

Last year I purchased a Polar watch that tracks my vitals during workouts. I used the Polar Flow website to obtain a copy of my data. For privacy reasons I shall not be sharing the dataset.

[4]:
```
path = './data/'
```

First, we create a list of files in the download.

[5]:
```
files = [f for f in listdir(path) if isfile(join(path, f))]
```

We shall only consider files containing the string `'training-session'`.

[6]:
```
files = [f for f in files if 'training-session' in f]
```

The number of files under consideration is:

[7]:
```
len(files)
```

[7]: 284

We loop over each of the files and them to a list.

[8]:
```
data = []

for f in files:
    with open(join(path, f)) as f:
        d = json.load(f)
        data.append(d)
```

We define a function to extract statistics about heart rate measured during the workouts.

[9]:
```
quantiles = [0.01, 0.25, 0.5, 0.75, 0.99]
```

[10]:
```
def extract_hr_info(workout, quantiles):

    stats = {'heartRateAvg2': np.nan,
             'heartRateStd': np.nan}

    for q in quantiles:
        stats[f'heartRateQ' + str(int(q * 100))] = np.nan

    # Check if data exists
    try:
        heart_rates = workout['exercises'][0]['samples']['heartRate']
    except KeyError:
        return stats

    # Loop over measurements
```

```
    hr_data = []
    for hr in heart_rates:

        # Check if actually measured hr
        if 'value' in hr:
            hr_data.append(hr['value'])

    stats['heartRateAvg2'] = np.mean(hr_data)
    stats['heartRateStd'] = np.std(hr_data)

    for q in quantiles:
        stats[f'heartRateQ' + str(int(q * 100))] = np.quantile(hr_data, q)

    return stats
```

We extract the relevant information from the items in the list.

[11]:
```
workouts = []

for d in data:
    basic = d['exercises'][0]
    hr = extract_hr_info(workout=d,
                         quantiles=quantiles)

    workouts.append({**basic, **hr})
```

Finally we create a dataframe containing the workout information.

[12]:
```
df = pd.DataFrame(workouts)
```

4 Data structure

We find the following columns in the dataframe.

[13]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284 entries, 0 to 283
Data columns (total 24 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   startTime       284 non-null    object
 1   stopTime        284 non-null    object
 2   timezoneOffset  284 non-null    int64
 3   duration        284 non-null    object
 4   sport           284 non-null    object
 5   kiloCalories    283 non-null    float64
 6   heartRate       283 non-null    object
```

```
 7   zones           284 non-null    object
 8   samples         284 non-null    object
 9   heartRateAvg2   283 non-null    float64
 10  heartRateStd    283 non-null    float64
 11  heartRateQ1     283 non-null    float64
 12  heartRateQ25    283 non-null    float64
 13  heartRateQ50    283 non-null    float64
 14  heartRateQ75    283 non-null    float64
 15  heartRateQ99    283 non-null    float64
 16  distance        130 non-null    float64
 17  latitude        130 non-null    float64
 18  longitude       130 non-null    float64
 19  ascent          120 non-null    float64
 20  descent         121 non-null    float64
 21  speed           130 non-null    object
 22  autoLaps        102 non-null    object
 23  laps            2 non-null      object
dtypes: float64(13), int64(1), object(10)
memory usage: 53.4+ KB
```

We remove columns that containt data from features I do not use in my training.

Due to privacy concerns I shan't be extracting longitudinal and latitudinal data.

[14]:
```
df = df.drop(['zones', 'samples', 'autoLaps',
              'laps', 'latitude', 'longitude',
              'ascent', 'descent'], axis=1)
```

[15]:
```
df.head()
```

[15]:
```
                 startTime                 stopTime  timezoneOffset  \
0  2019-05-24T13:18:14.000  2019-05-24T14:58:44.125             120
1  2019-05-04T12:03:34.000  2019-05-04T13:21:38.500             120
2  2019-04-12T12:48:57.000  2019-04-12T12:59:10.750             120
3  2019-06-12T13:13:09.000  2019-06-12T13:23:15.500             120
4  2019-05-24T14:59:06.000  2019-05-24T15:29:08.750             120

      duration             sport  kiloCalories  \
0  PT6030.125S  STRENGTH_TRAINING        658.00
1  PT4684.500S  STRENGTH_TRAINING        373.00
2   PT613.750S  TREADMILL_RUNNING         62.00
3   PT606.500S  TREADMILL_RUNNING         71.00
4  PT1802.750S  TREADMILL_RUNNING        416.00

                              heartRate  heartRateAvg2  heartRateStd  \
0  {'min': 72, 'avg': 105, 'max': 136}         104.77         11.28
1   {'min': 71, 'avg': 99, 'max': 138}          98.65         12.51
2   {'min': 71, 'avg': 97, 'max': 107}          97.07          8.00
```

```
3  {'min': 67, 'avg': 105, 'max': 121}        105.24         11.25
4  {'min': 84, 'avg': 144, 'max': 170}        143.85         18.47

   heartRateQ1  heartRateQ25  heartRateQ50  heartRateQ75  heartRateQ99  \
0        77.00         99.00        105.00        111.00        132.00
1        74.00         91.00         97.00        106.00        126.00
2        72.00         94.00         97.00        104.00        107.00
3        67.96         98.00        104.00        118.00        121.00
4        87.00        133.00        146.00        158.00        169.00

   distance speed
0       nan   NaN
1       nan   NaN
2       nan   NaN
3       nan   NaN
4       nan   NaN
```

5 Missing Values

The watch tracks different information for different workouts. For example when walking it tracks location but when walking on a treadmill it doesn't, hence there is quite a lot of missing data.

[16]:
```
missing = (df.isna().sum() / df.shape[0] * 100)
missing.name = 'Percent missing'
missing = missing.to_frame()
missing = missing.sort_values('Percent missing', ascending=False)
missing = missing[missing['Percent missing'] > 0]
missing = missing.reset_index()
missing = missing.rename(columns={'index': 'Feature'})
np.round(missing, 2)
```

[16]:

	Feature	Percent missing
0	distance	54.23
1	speed	54.23
2	kiloCalories	0.35
3	heartRate	0.35
4	heartRateAvg2	0.35
5	heartRateStd	0.35
6	heartRateQ1	0.35
7	heartRateQ25	0.35
8	heartRateQ50	0.35
9	heartRateQ75	0.35
10	heartRateQ99	0.35

6 Transforms

We apply certain transforms to make the data easier to work with. First we convert strings to datetimes.

[17]:
```
df['startTime'] = pd.to_datetime(df['startTime'])
df['stopTime'] = pd.to_datetime(df['stopTime'])
```

We calculate the total duration of each individual workout in minutes.

[18]:
```
df['totalTime'] = (df['stopTime'] - df['startTime'])
df['totalTime'] = df['totalTime'].apply(lambda x: round(x.seconds / 60, 2))
df.drop('duration', axis=1, inplace=True)
```

We extract maximum, average and minimum heart rate values from the `heartRate` column.

[19]:
```
df['heartRateMax'] = df['heartRate'].apply(lambda x: x['max'] if isinstance(x,␣
 ↪dict) else np.nan)
df['heartRateAvg'] = df['heartRate'].apply(lambda x: x['avg'] if isinstance(x,␣
 ↪dict) else np.nan)
df['heartRateMin'] = df['heartRate'].apply(lambda x: x['min'] if isinstance(x,␣
 ↪dict) else np.nan)
df.drop('heartRate', axis=1, inplace=True)
```

We assume that if there is no `distance` then the workout was indoors:

[20]:
```
df['isInside'] = df['distance'].apply(lambda x: True if pd.isnull(x) else False)
df = df.drop(['distance', 'speed'], axis=1)
```

We are going to map sports to different `activityType`'s. We will map strength training to `1` and cardiovascular work to `0`.

[21]:
```
def sport_to_activity_type(x):
    if 'strength' in x.lower():
        return True
    else:
        return False
```

[22]:
```
df['isStrength'] = df['sport'].apply(sport_to_activity_type)
```

[23]:
```
df['sport'] = df['sport'].apply(lambda x: x.lower())
df['sport'] = pd.Categorical(df['sport'])
```

We extract a list of unique `sport` values:

[24]:
```
sports = sorted(list(df['sport'].unique()))
```

We reorder the alphabetically

[25]:
```
order = sorted(df.columns.to_list())
```

[26]:
```
df = df[order]
```

We check if there are any more NaN's in the data.

[27]:
```
df.isna().sum()
```

[27]:
```
heartRateAvg      1
heartRateAvg2     1
heartRateMax      1
heartRateMin      1
heartRateQ1       1
heartRateQ25      1
heartRateQ50      1
heartRateQ75      1
heartRateQ99      1
heartRateStd      1
isInside          0
isStrength        0
kiloCalories      1
sport             0
startTime         0
stopTime          0
timezoneOffset    0
totalTime         0
dtype: int64
```

There is one row with NaN's. This might due to my watch having little battery left to make the measurements.

[28]:
```
df = df.dropna()
```

We proceed to sort the data with the latest workouts at the top of the dataframe.

[29]:
```
sort_cols = ['startTime','startTime']
df = df.sort_values(sort_cols, ascending=False)
df = df.reset_index(drop=True)
```

We verify that the datatypes are correct.

[30]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 283 entries, 0 to 282
Data columns (total 18 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   heartRateAvg    283 non-null    float64
 1   heartRateAvg2   283 non-null    float64
 2   heartRateMax    283 non-null    float64
```

```
 3   heartRateMin    283 non-null    float64
 4   heartRateQ1     283 non-null    float64
 5   heartRateQ25    283 non-null    float64
 6   heartRateQ50    283 non-null    float64
 7   heartRateQ75    283 non-null    float64
 8   heartRateQ99    283 non-null    float64
 9   heartRateStd    283 non-null    float64
 10  isInside        283 non-null    bool
 11  isStrength      283 non-null    bool
 12  kiloCalories    283 non-null    float64
 13  sport           283 non-null    category
 14  startTime       283 non-null    datetime64[ns]
 15  stopTime        283 non-null    datetime64[ns]
 16  timezoneOffset  283 non-null    int64
 17  totalTime       283 non-null    float64
dtypes: bool(2), category(1), datetime64[ns](2), float64(12), int64(1)
memory usage: 34.3 KB
```

[31]:
```
df.head()
```

[31]:
```
   heartRateAvg  heartRateAvg2  heartRateMax  heartRateMin  heartRateQ1  \
0        102.00         102.03        116.00         69.00        73.00
1        104.00         104.14        132.00         70.00        73.81
2        103.00         103.10        122.00         87.00        91.00
3        108.00         107.97        125.00         87.00        91.00
4        117.00         117.08        141.00         90.00        92.00

   heartRateQ25  heartRateQ50  heartRateQ75  heartRateQ99  heartRateStd  \
0         96.00        103.00        109.00        115.00          9.02
1         86.00        110.50        118.00        131.00         16.67
2         96.00        101.00        110.00        120.00          7.94
3        103.00        108.00        114.00        124.00          7.46
4        103.00        120.00        128.00        141.00         13.76

   isInside  isStrength  kiloCalories    sport           startTime  \
0     False       False        245.00  walking 2020-03-29 21:50:21
1     False       False        401.00  walking 2020-03-27 20:38:32
2     False       False        336.00  walking 2020-03-26 21:07:46
3     False       False        380.00  walking 2020-03-25 19:22:38
4     False       False        358.00  walking 2020-03-24 13:09:06

                 stopTime  timezoneOffset  totalTime
0 2020-03-29 22:23:41.750             120      33.33
1 2020-03-27 21:25:03.750              60      46.52
2 2020-03-26 21:52:55.625              60      45.15
3 2020-03-25 20:10:17.875              60      47.65
4 2020-03-24 13:48:46.750              60      39.67
```

7 Data analysis

Given that we have produced a clean dataset we can proceed to analyse a few aspects.

7.1 Time span

The date of the first workout is:

[32]:
```
str(df['startTime'].min())
```

[32]:
```
'2019-02-20 20:46:35'
```

The date of the last workout is:

[33]:
```
str(df['startTime'].max())
```

[33]:
```
'2020-03-29 21:50:21'
```

Workouts measured:

[34]:
```
len(df)
```

[34]:
```
283
```

7.2 Descriptive statistics

[35]:
```
df.drop('timezoneOffset', axis=1).describe()
```

[35]:
```
       heartRateAvg  heartRateAvg2  heartRateMax  heartRateMin  heartRateQ1  \
count        283.00         283.00        283.00        283.00       283.00
mean         105.19         105.24        128.34         76.74        80.61
std           11.87          11.86         18.25          8.99         8.40
min           82.00          81.98         93.00         53.00        54.00
25%           96.00          96.42        115.00         70.00        75.00
50%          103.00         103.42        125.00         77.00        80.00
75%          111.00         111.26        138.50         83.00        86.00
max          148.00         148.35        178.00         99.00       107.00

       heartRateQ25  heartRateQ50  heartRateQ75  heartRateQ99  heartRateStd  \
count        283.00        283.00        283.00        283.00        283.00
mean          98.24        105.55        112.64        125.84         10.52
std           10.69         12.26         14.36         18.06          4.46
min           77.00         82.00         87.00         92.00          2.96
25%           91.00         97.00        102.00        113.00          7.58
50%           97.00        104.00        111.00        123.00         10.00
75%          103.00        112.00        119.00        135.00         12.25
max          146.00        151.00        160.00        177.00         27.10

       kiloCalories  totalTime
```

```
count         283.00     283.00
mean          315.98      42.83
std           218.75      29.65
min            29.00       5.00
25%           121.50      15.92
50%           277.00      36.45
75%           441.50      65.29
max         1,067.00     172.73
```

7.3 Kilocalories burned in total

First we count the total `kiloCalories` I burned during the period in question.

[36]:
```python
total_calories = df['kiloCalories'].sum()
print(total_calories)
```

```
89421.0
```

We convert this number to kilograms of body fat. According to this article it equates to

[37]:
```python
def kcal_to_kg(x):
    return round(x / 7700, 2)
```

[38]:
```python
kcal_to_kg(total_calories)
```

[38]:
```
11.61
```

7.4 Kilocalories burned by sport

[39]:
```python
by_sport = df[['kiloCalories', 'sport']].groupby('sport', as_index=False)
by_sport = by_sport.sum()
by_sport['sport'] = by_sport['sport'].apply(lambda x: x.lower())
by_sport['kiloCalories'] = by_sport['kiloCalories'].astype(int)
by_sport = by_sport.rename(columns={'kiloCalories': 'Total kilocalories',␣
 ↪'sport': 'Sport'})
by_sport = by_sport.sort_values('Total kilocalories', ascending=False)
by_sport['Total kilograms'] = by_sport['Total kilocalories'].apply(kcal_to_kg)

by_sport = by_sport.style.background_gradient(cmap='YlGn', subset='Total␣
 ↪kilograms')
by_sport = by_sport.set_precision(2)

by_sport
```

[39]:
```
<pandas.io.formats.style.Styler at 0x7f1cea8d0ee0>
```

7.5 Kilocalories burned over time

Next we produce a plot of `kiloCalories` burned over a two month period in 2019. First we extract the relevant data.

[40]:
```
start = pd.to_datetime('2019-04-1')
stop = pd.to_datetime('2019-06-1')

daily = df[['startTime', 'kiloCalories']]
mask = (daily['startTime'] >= start) & (daily['startTime'] < stop)
daily = daily[mask]
daily['startTime'] = daily['startTime'].dt.date
daily = daily.groupby('startTime', as_index=False)
daily = daily.sum()
daily = daily.sort_values('startTime', ascending=False)
daily['startTime'] = pd.to_datetime(daily['startTime'])
daily = daily.reset_index(drop=True)
```

We create a dataframe with all the dates to perform a left join and fill the `NaN`'s with zeroes.

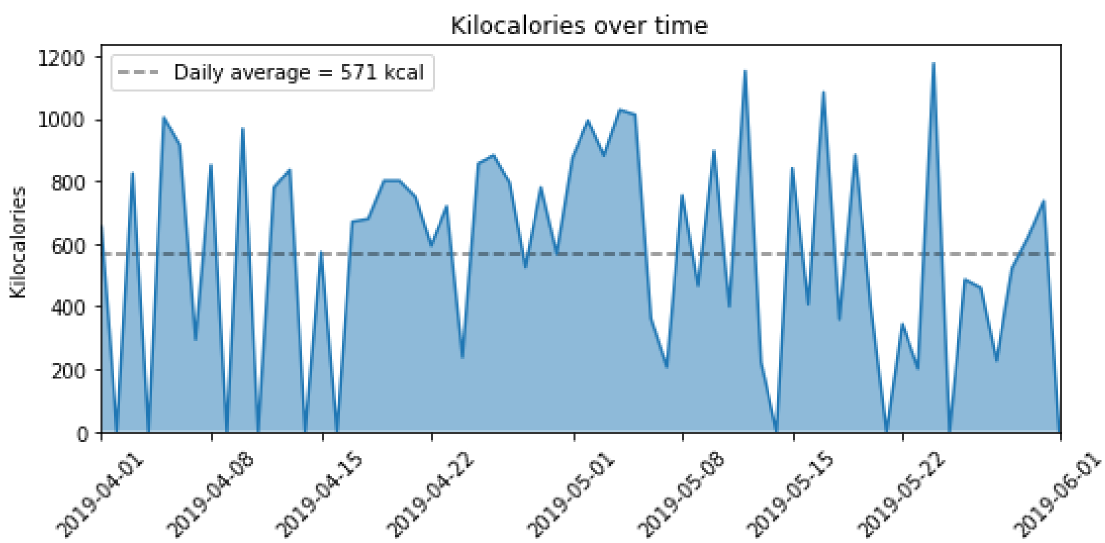
[41]:
```
dates = pd.date_range(start, stop)
dates = dates.to_frame()
dates = dates.reset_index(drop=True)
dates.columns = ['startTime']
```

[42]:
```
daily = pd.merge(dates, daily, on='startTime', how='left')
daily = daily.fillna(0)
```

Finally we produce the figure:

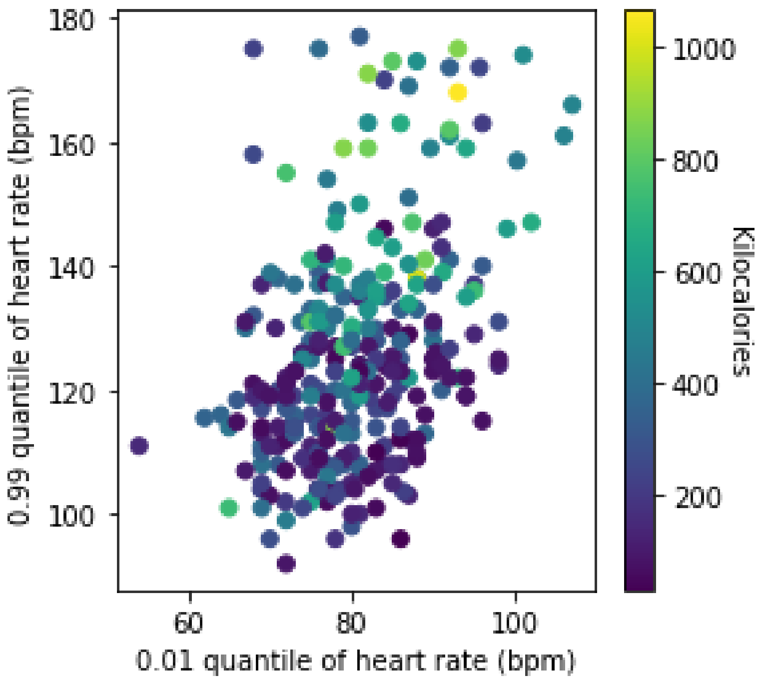
[43]:
```
width = 800
height = 400
dpi = 100

plt.figure(figsize=(width/dpi, height/dpi))
plt.plot(daily['startTime'], daily['kiloCalories'])

plt.fill_between(x=daily['startTime'],
                 y1=0,
                 y2=daily['kiloCalories'],
                 alpha=1/2)

daily_avg = daily['kiloCalories'].mean()

plt.hlines(xmin=daily['startTime'].min(),
           xmax=daily['startTime'].max(),
           y=daily_avg,
           linestyle='dashed',
           label=f'Daily average = {round(daily_avg)} kcal',
```

```
            alpha=1/2)

plt.title('Kilocalories over time')
plt.xticks(rotation=45, horizontalalignment='center')
plt.xlim(daily['startTime'].min(), daily['startTime'].max())
plt.ylim(0, daily['kiloCalories'].max() * 1.05)
plt.ylabel('Kilocalories')
plt.legend(loc='best')
plt.tight_layout()
plt.savefig('./img/kilocalories_ts.png')
plt.show()
```



7.6 Kilocalories by intensity

[44]:
```
plt.scatter(df['heartRateQ1'], df['heartRateQ99'], c=df['kiloCalories'])
plt.xlabel('0.01 quantile of heart rate (bpm)')
plt.ylabel('0.99 quantile of heart rate (bpm)')

cbar = plt.colorbar()
cbar.set_label('Kilocalories', rotation=270)
plt.savefig('./img/intensity_scatter.png')
plt.show()
```



7.7 Workouts by sport

We check how many workouts I completed.

[45]:
```python
stats = df[['sport', 'startTime']]
stats = stats.groupby(['sport'], as_index=False)
stats = stats.count()
stats = stats.rename(columns={'sport': 'Sport',
                              'startTime': 'Count'})
stats = stats.sort_values('Count', ascending=False)

stats = stats.style.background_gradient(cmap='YlGn', subset='Count')
stats = stats.set_precision(2)

stats
```

[45]:
```
<pandas.io.formats.style.Styler at 0x7f1cea8bf610>
```

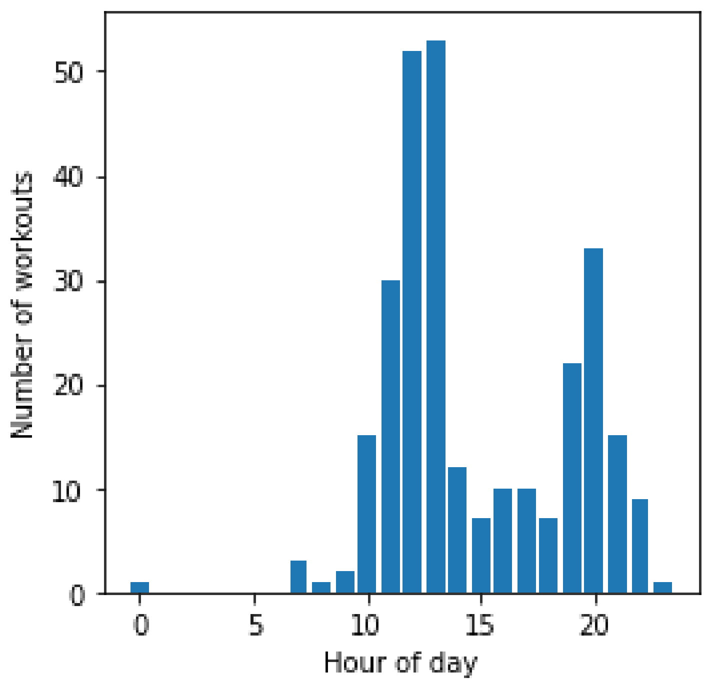
7.8 By hour of day

We count workouts by hour of day.

[46]:
```python
by_hour = df[['startTime', 'sport']].copy()
by_hour['startHour'] = by_hour['startTime'].dt.hour
by_hour = by_hour.drop('startTime', axis=1)
```

```
by_hour = by_hour.groupby('startHour', as_index=False)
by_hour = by_hour.count()

all_hours = pd.DataFrame(range(0, 24), columns=['startHour'])

by_hour = pd.merge(all_hours, by_hour, how='left')
by_hour = by_hour.fillna(0)
by_hour = by_hour.sort_values('startHour')
by_hour = by_hour.rename(columns={'startHour': 'Hour of day',
                                  'sport': 'Total workouts'})
```

[47]:
```
plt.bar(by_hour['Hour of day'], by_hour['Total workouts'])
plt.ylabel('Number of workouts')
plt.xlabel('Hour of day')
plt.savefig('./img/workouts_by_hour_of_day.png')
plt.show()
```



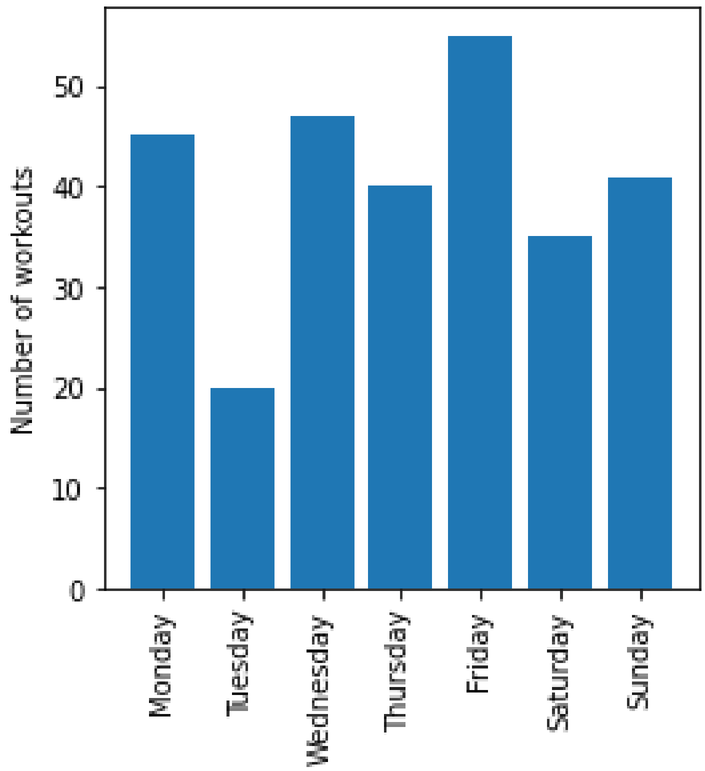
7.9 By day of week

We count workouts by day of week.

[48]:
```
by_day = df[['startTime', 'sport']].copy()
by_day['Day of week'] = pd.to_datetime(by_day['startTime']).dt.day_name()
by_day['Day number'] = pd.to_datetime(by_day['startTime']).dt.dayofweek
by_day = by_day.groupby(['Day of week', 'Day number'], as_index=False)
```

```
by_day = by_day.count()
by_day = by_day.drop('startTime', axis=1)
by_day = by_day.sort_values('Day number')
by_day = by_day.rename(columns={'sport': 'Total Workouts'})
```

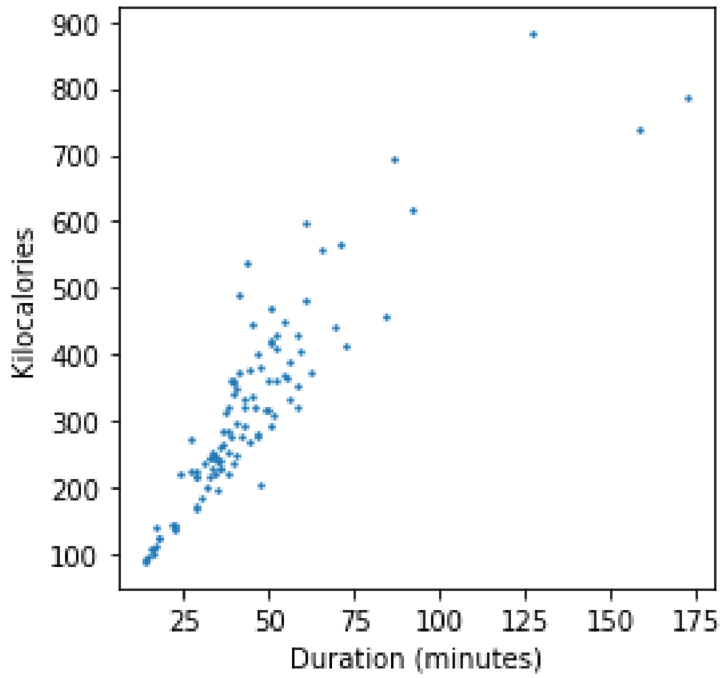
[49]:
```
plt.bar(by_day['Day of week'], by_day['Total Workouts'])
plt.xticks(rotation=90)
plt.ylabel('Number of workouts')
plt.savefig('./img/workouts_by_day_of_week.png')
plt.show()
```



7.10 Scatter plot of walks data

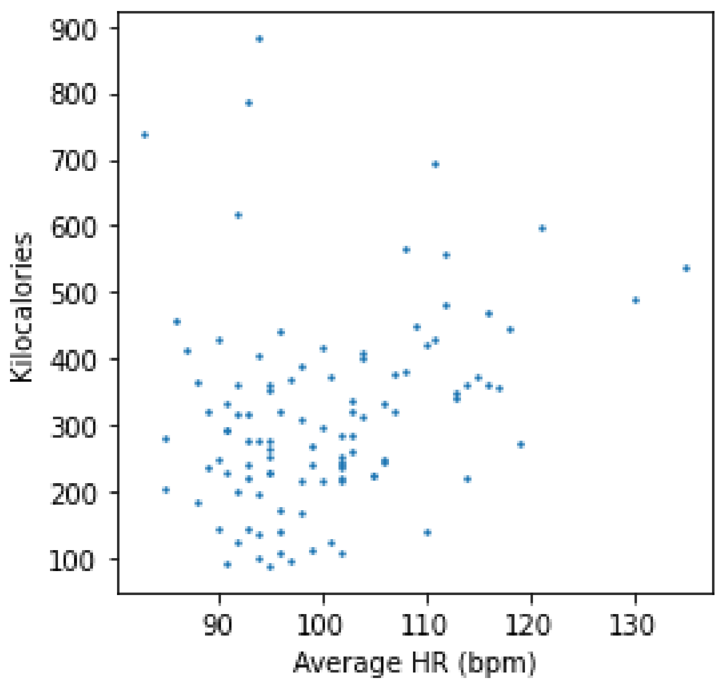
We plot `totalTime` versus `kiloCalories`. As can be seen their seems to exist a linear relationship between the two.

[50]:
```
walking = df[df['sport'] == 'walking']
plt.scatter(walking['totalTime'], walking['kiloCalories'], s=2)
plt.xlabel('Duration (minutes)')
plt.ylabel('Kilocalories')
plt.savefig('./img/walks_kilocalories_vs_time.png')
plt.show()
```



We plot `heartRateAvg` against `kiloCalories`. Again we see a linear relationship although there are a couple of outliers

[51]:
```
walking = df[df['sport'] == 'walking']
plt.scatter(walking['heartRateAvg'], walking['kiloCalories'], s=2)
plt.ylabel('Kilocalories')
plt.xlabel('Average HR (bpm)')
plt.savefig('./img/walks_kilocalories_vs_avg_hr.png')
plt.show()
```



8 Regression

8.1 Data preparation

Now we proceed to build a regression model to predict `kiloCalories` burned during a workout. First we create a subset of the original data.

[52]:
```
reg_df = df[['kiloCalories', 'totalTime',
             'heartRateQ99', 'isStrength', 'sport']].copy()
```

[53]:
```
reg_df.head()
```

[53]:

	kiloCalories	totalTime	heartRateQ99	isStrength	sport
0	245.00	33.33	115.00	False	walking
1	401.00	46.52	131.00	False	walking
2	336.00	45.15	120.00	False	walking
3	380.00	47.65	124.00	False	walking
4	358.00	39.67	141.00	False	walking

We remove the rows where `sport` is `running` because there were only two workouts recorded during the period in question.

[54]:
```
reg_df = reg_df[reg_df['sport'] != 'running']
```

8.1.1 Outliers

The data is cleansed of outliers using interquartile range.

[55]:
```python
def is_outlier_iqr(series, k=1.5):
    """
    Check if value is an outlier
    using interquartile range.
    """

    q1 = series.quantile(0.25)
    q3 = series.quantile(0.75)
    iqr = q3 - q1
    is_outlier = (series <= q1 - k * iqr) | (q3 + k * iqr <= series)

    return is_outlier
```

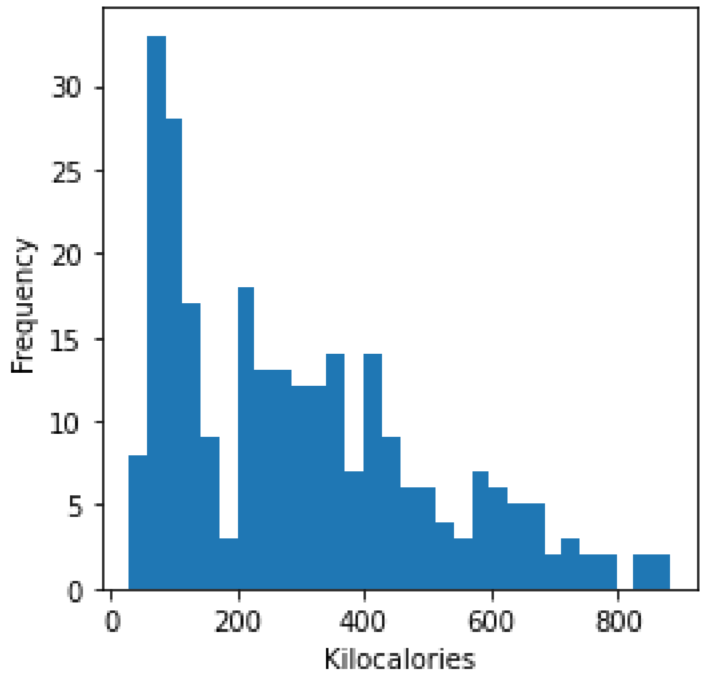
[56]:
```python
time_mask = is_outlier_iqr(series=reg_df['totalTime'])
kcal_mask = is_outlier_iqr(series=reg_df['kiloCalories'])
hr_mask = is_outlier_iqr(series=reg_df['heartRateQ99'])
```

[57]:
```python
reg_df = reg_df[~(time_mask | kcal_mask | hr_mask)]
```

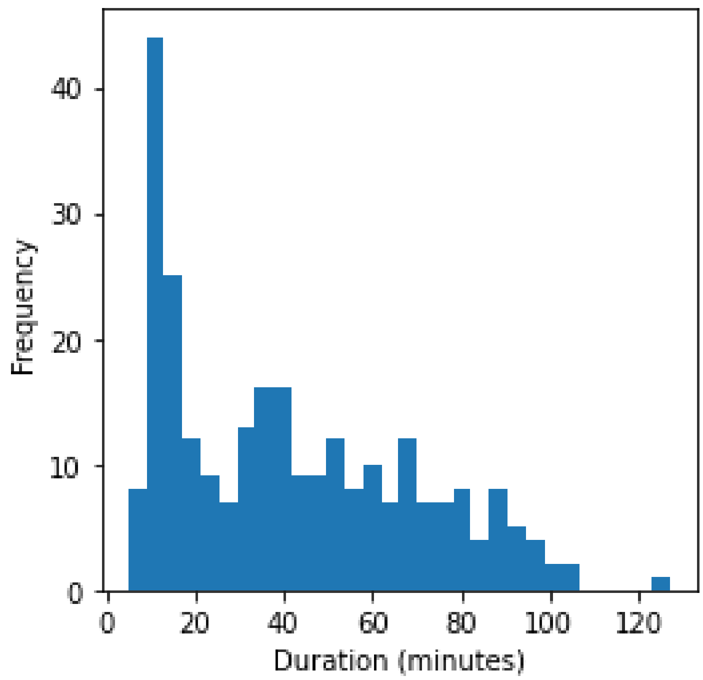
8.2 Histograms

We proceed to visualize histograms of each of the variables.

[58]:
```python
plt.hist(reg_df['kiloCalories'], bins=30)
plt.xlabel('Kilocalories')
plt.ylabel('Frequency')
plt.savefig('./img/kilocalories_histogram.png')
plt.show()
```

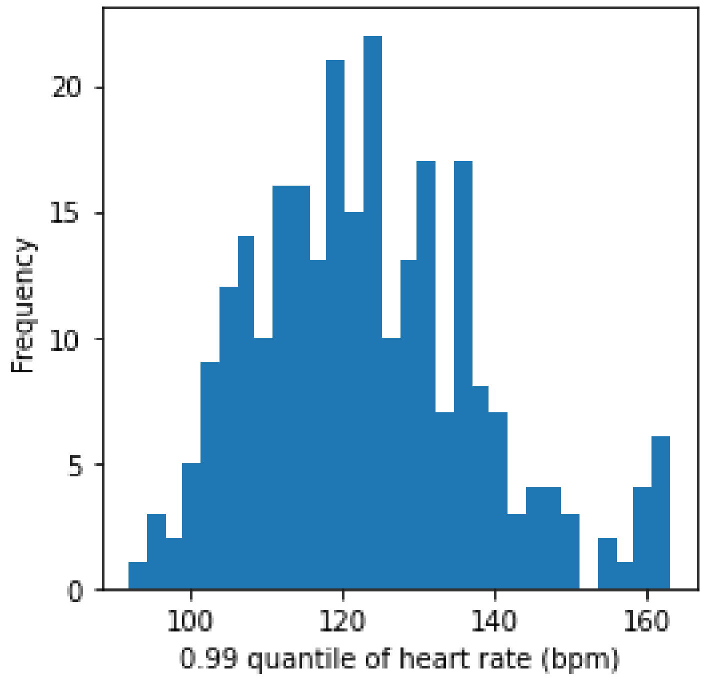


[59]:
```
plt.hist(reg_df['totalTime'], bins=30)
plt.xlabel('Duration (minutes)')
plt.ylabel('Frequency')
plt.savefig('./img/duration_histogram.png')
plt.show()
```



[60]:

```
plt.hist(reg_df['heartRateQ99'], bins=30)
plt.xlabel('0.99 quantile of heart rate (bpm)')
plt.ylabel('Frequency')
plt.savefig('./img/q99_hr_histogram.png')
plt.show()
```

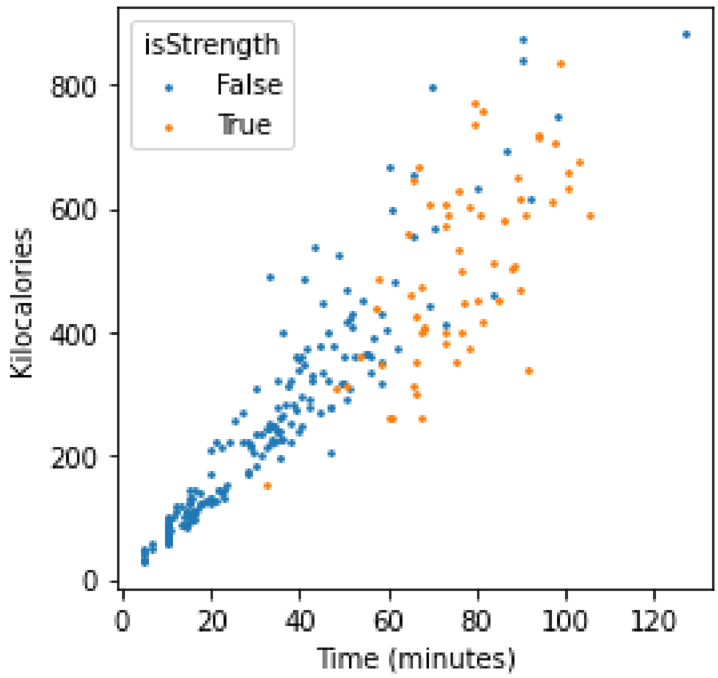


8.3 Scatter plots

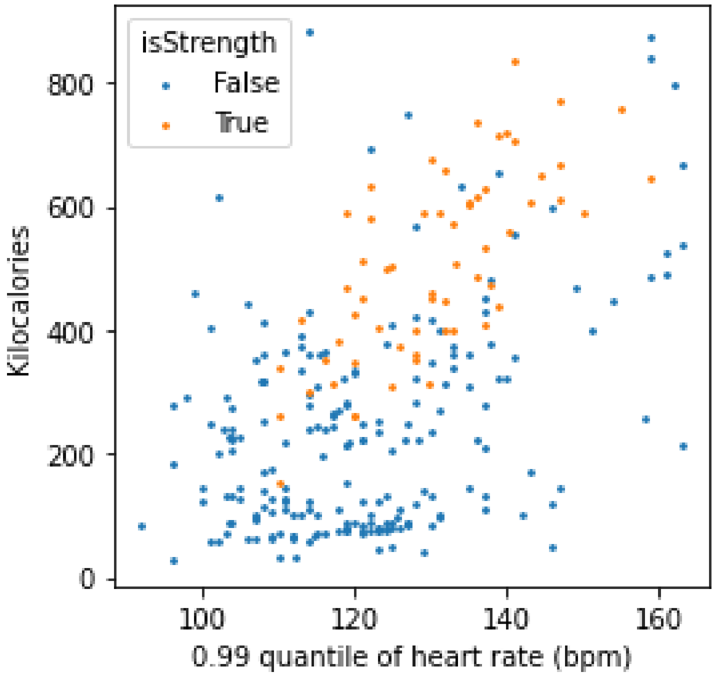
The plot below gives reason to suspect a linear relationship between `kiloCalories` and `totalTime`.

[61]:

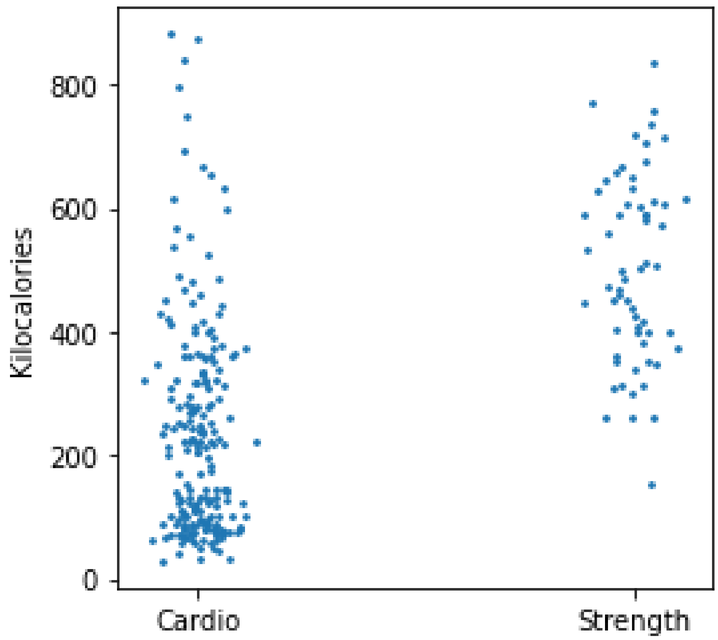
```
for val in [False, True]:
    tmp = reg_df[reg_df['isStrength'] == val]
    plt.scatter(tmp['totalTime'],
                tmp['kiloCalories'],
                s=3,
                label=val)

plt.xlabel('Time (minutes)')
plt.ylabel('Kilocalories')
plt.legend(title='isStrength', loc='best')
plt.savefig('./img/time_vs_kilocalories_scatter_by_strength.png')
plt.show()
```



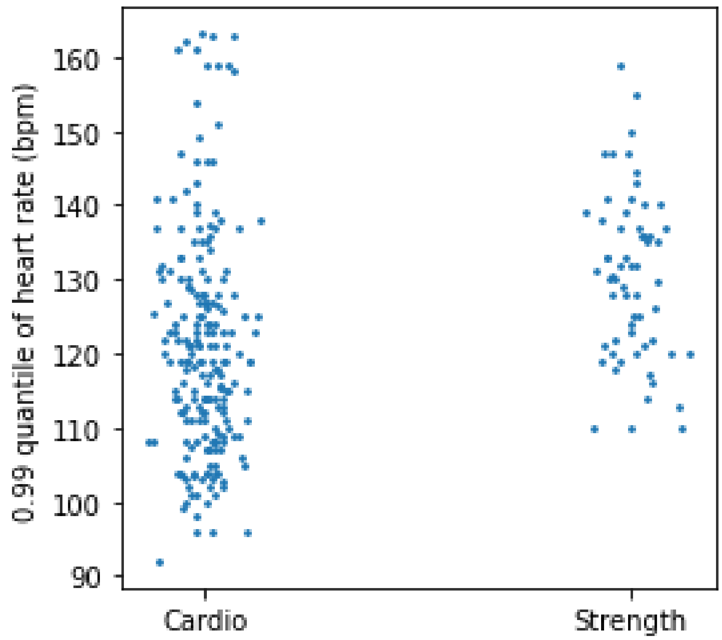
[62]:
```
for val in [False, True]:
    tmp = reg_df[reg_df['isStrength'] == val]
    plt.scatter(tmp['heartRateQ99'],
                tmp['kiloCalories'],
                s=3,
                label=val)

plt.xlabel('0.99 quantile of heart rate (bpm)')
plt.ylabel('Kilocalories')
plt.legend(title='isStrength', loc='best')
plt.savefig('./img/99q_hr_vs_kilocalories_scatter_by_strength.png')
plt.show()
```



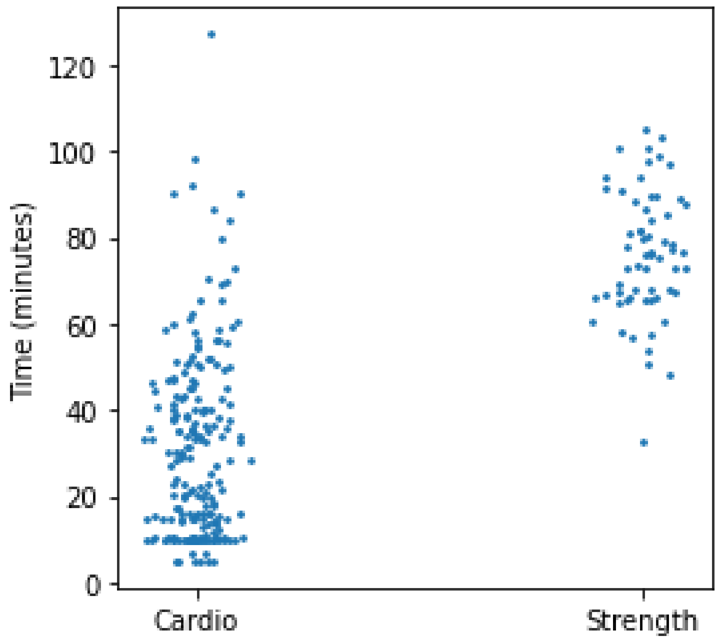
[63]:
```
plt.scatter(reg_df['isStrength'] + np.random.normal(scale=1/20,␣
↪size=len(reg_df)),
            reg_df['kiloCalories'], s=3)

plt.ylabel('Kilocalories')
plt.xticks(ticks=[0, 1], labels=['Cardio', 'Strength'])
plt.savefig('./img/is_strength_vs_kilocalories_jitter.png')
plt.show()
```



[64]:
```
plt.scatter(reg_df['isStrength'] + np.random.normal(scale=1/20,␣
↪size=len(reg_df)),
            reg_df['heartRateQ99'], s=3)

plt.ylabel('0.99 quantile of heart rate (bpm)')
plt.xticks(ticks=[0, 1], labels=['Cardio', 'Strength'])
plt.savefig('./img/is_strength_vs_99q_hr_scatter.png')
plt.show()
```



[65]:
```
plt.scatter(reg_df['isStrength'] + np.random.normal(scale=1/20,␣
↪size=len(reg_df)),
            reg_df['totalTime'], s=3)

plt.ylabel('Time (minutes)')
plt.xticks(ticks=[0, 1], labels=['Cardio', 'Strength'])
plt.savefig('./img/is_strength_vs_time_jitter.png')
plt.show()
```



8.4 Correlation

We convert binary the feature `isStrength` to integers for the rest of the analysis.

[66]:
```
reg_df['isStrength'] = reg_df['isStrength'].astype(int)
```

We inspect the correlation matrix to check for multicollinearity. It should be noted that the correlation between `kiloCalories` and `totalTime` is quite high and this to be expected.

[67]:
```
C = reg_df.corr(method='pearson')
C = C.style.background_gradient(cmap='YlGn')
C = C.set_precision(2)
C
```

[67]:
```
<pandas.io.formats.style.Styler at 0x7f1ce7943d90>
```

8.5 Multicollinearity

We inspect the respect variance inflation factors and are happy to see that all are below 10.

[68]:
```
tmp = reg_df.drop(['kiloCalories', 'sport'], axis=1)

vifs = []
for i in range(tmp.shape[1]):
    vif = variance_inflation_factor(tmp.to_numpy(), i)
    vifs.append(round(vif, 2))
```

```python
vifs = pd.DataFrame(vifs, index=tmp.columns, columns=['VIF'])
vifs = vifs.sort_values('VIF', ascending=False)
vifs = vifs.reset_index()
vifs = vifs.rename(columns={'index': 'Variable'})
vifs = vifs.style.background_gradient(cmap='OrRd')
vifs = vifs.set_precision(2)

vifs
```

[68]: <pandas.io.formats.style.Styler at 0x7f1cea938d60>

8.6 Modelling

Before the actual modelling we prepare a function to calculate `RMSE` to compare models and extract the true `kiloCalories` into a separate array.

[69]:
```python
y_true = reg_df['kiloCalories'].to_numpy()
```

[70]:
```python
def calc_rmse(y_true, y_pred):
    x = np.sqrt(np.mean(np.power(y_true - y_pred, 2)))
    return round(x, 4)
```

[71]:
```python
all_results = []
```

8.6.1 Time only

We start the modelling section of by building the simplest model that comes to mind: predict `kiloCalories` using `totalTime`.

[72]:
```python
formula = 'kiloCalories ~ totalTime'
mdl_time = smf.ols(formula=formula, data=reg_df)
mdl_time = mdl_time.fit()
mdl_time.summary2()
```

[72]:
```
<class 'statsmodels.iolib.summary2.Summary'>
"""
                 Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.849
Dependent Variable: kiloCalories     AIC:                3070.3883
Date:               2020-10-02 21:09 BIC:                3077.5477
No. Observations:   265              Log-Likelihood:     -1533.2
Df Model:           1                F-statistic:        1483.
Df Residuals:       263              Prob (F-statistic): 4.24e-110
R-squared:          0.849            Scale:              6254.0
-------------------------------------------------------------------
```

```
                 Coef.   Std.Err.     t     P>|t|    [0.025   0.975]
--------------------------------------------------------------------
Intercept      17.1713    8.7686   1.9583  0.0513  -0.0942  34.4369
totalTime       6.7722    0.1759  38.5076  0.0000   6.4260   7.1185
-------------------------------------------------------------------
Omnibus:               35.699       Durbin-Watson:          1.803
Prob(Omnibus):         0.000        Jarque-Bera (JB):       92.425
Skew:                  0.605        Prob(JB):               0.000
Kurtosis:              5.628        Condition No.:          90
===================================================================

"""
```

[73]:
```python
y_pred = mdl_time.predict(reg_df)
rmse = calc_rmse(y_pred, y_true)
all_results.append((rmse, formula))
```

[74]:
```python
print(rmse)
```

```
78.7832
```

8.6.2 By sport

The next regression we are going to do will be univariate regression separately for each sport, this will help us answer the question which sport is the most effective at burning calories during a workout.

[75]:
```python
all_sports = sorted(reg_df['sport'].unique())
reg_sports_res = []

# For all sport do simple linear regression
for sport in all_sports:
    tmp = reg_df[reg_df['sport'] == sport]
    formula = 'kiloCalories ~ totalTime'
    mdl_sport = smf.ols(formula=formula, data=tmp)
    mdl_sport = mdl_sport.fit()
    sport_stats = [formula, sport] + list(mdl_sport.params) + [mdl_sport.
 ↪rsquared]
    reg_sports_res.append(sport_stats)

cols = ['Formula', 'Sport', 'Intercept', 'Slope', 'R squared']

reg_sports_res = pd.DataFrame(reg_sports_res, columns=cols)
reg_sports_res = reg_sports_res.sort_values(['Slope'], ascending=False)
reg_sports_res = reg_sports_res.reset_index(drop=True)

readme_df = reg_sports_res.copy().round(2)
```

```
reg_sports_res = reg_sports_res.style.background_gradient(cmap='YlGn',␣
↪subset='Slope')
reg_sports_res = reg_sports_res.set_precision(2)

reg_sports_res
```

[75]: <pandas.io.formats.style.Styler at 0x7f1d2c8c7f70>

8.7 Time and heart rate

We try to enhance the model by adding `heartRateQ99`.

[76]:
```
formula = 'kiloCalories ~ totalTime + heartRateQ99'
mdl_time_and_hr = smf.ols(formula=formula, data=reg_df)
mdl_time_and_hr = mdl_time_and_hr.fit()
mdl_time_and_hr.summary2()
```

[76]:
```
<class 'statsmodels.iolib.summary2.Summary'>
"""
                  Results: Ordinary least squares
=================================================================
Model:              OLS              Adj. R-squared:     0.918
Dependent Variable: kiloCalories     AIC:                2910.3348
Date:               2020-10-02 21:09 BIC:                2921.0740
No. Observations:   265              Log-Likelihood:     -1452.2
Df Model:           2                F-statistic:        1472.
Df Residuals:       262              Prob (F-statistic): 3.32e-143
R-squared:          0.918            Scale:              3405.9
-----------------------------------------------------------------
               Coef.    Std.Err.    t     P>|t|    [0.025   0.975]
-----------------------------------------------------------------
Intercept    -420.7741  30.1664 -13.9484 0.0000 -480.1736 -361.3746
totalTime       6.2025   0.1353  45.8339 0.0000    5.9361    6.4690
heartRateQ99    3.7435   0.2519  14.8636 0.0000    3.2476    4.2394
-----------------------------------------------------------------
Omnibus:              14.259       Durbin-Watson:          1.917
Prob(Omnibus):        0.001        Jarque-Bera (JB):       21.717
Skew:                 -0.355       Prob(JB):               0.000
Kurtosis:             4.210        Condition No.:          1106
=================================================================
* The condition number is large (1e+03). This might indicate
strong multicollinearity or other numerical problems.
"""
```

[77]:
```
y_pred = mdl_time_and_hr.predict(reg_df)
rmse = calc_rmse(y_pred, y_true)
all_results.append((rmse, formula))
```

[78]:
```
print(rmse)
```

```
58.0287
```

8.8 Time with random effects by workout type

[79]:
```
formula = 'kiloCalories ~ totalTime + heartRateQ99'
re_formula = ' ~ totalTime'
group = 'isStrength'

mdl_time_with_hr_re = smf.mixedlm(formula=formula,
                  data=reg_df,
                  groups=reg_df[group],
                  re_formula=re_formula)

mdl_time_with_hr_re = mdl_time_with_hr_re.fit(method='lbfgs')
mdl_time_with_hr_re.summary()
```

[79]:
```
<class 'statsmodels.iolib.summary2.Summary'>
"""
                Mixed Linear Model Regression Results
======================================================================
Model:                  MixedLM     Dependent Variable:     kiloCalories
No. Observations:       265         Method:                 REML
No. Groups:             2           Scale:                  2570.3031
Min. group size:        61          Log-Likelihood:         -1416.8825
Max. group size:        204         Converged:              Yes
Mean group size:        132.5
----------------------------------------------------------------------
                         Coef.   Std.Err.   z    P>|z|  [0.025   0.975]
----------------------------------------------------------------------
Intercept               -475.991   65.174 -7.303 0.000 -603.730 -348.252
totalTime                  6.755    0.858  7.874 0.000    5.074    8.437
heartRateQ99               3.933    0.220 17.868 0.000    3.502    4.365
Group Var                210.604   51.671
Group x totalTime Cov      9.904    0.550
totalTime Var              0.466    0.036
======================================================================

"""
```

[80]:
```
y_pred = mdl_time_with_hr_re.predict(reg_df)
rmse = calc_rmse(y_pred, y_true)
all_results.append((rmse, formula, re_formula, group))
```

[81]:
```
print(rmse)
```

```
60.9247
```

8.9 Model evaluation

We compare the linear models created earlier:

[82]:
```
comp_df = pd.DataFrame(all_results, columns=['RMSE', 'Formula', 'Random␣
↪effects', 'Groups'])
comp_df = comp_df.sort_values('RMSE')

comp_df = comp_df.style.background_gradient(cmap='OrRd', subset='RMSE')
comp_df = comp_df.set_precision(2)

comp_df
```

[82]:
```
<pandas.io.formats.style.Styler at 0x7f1ce7a3ba60>
```

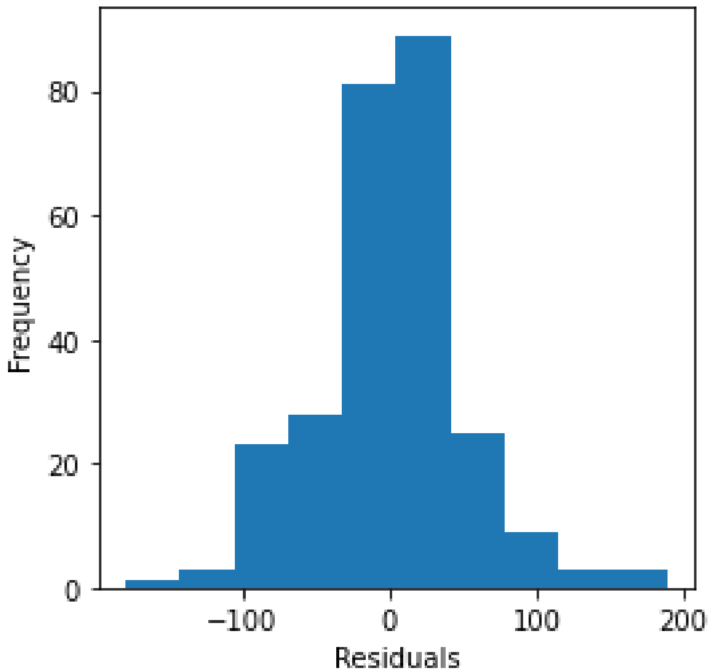
For further evaluation we choose the random effects model.

[83]:
```
mdl = mdl_time_with_hr_re
residuals = mdl_time_with_hr_re.resid
```

8.9.1 Visual inspection

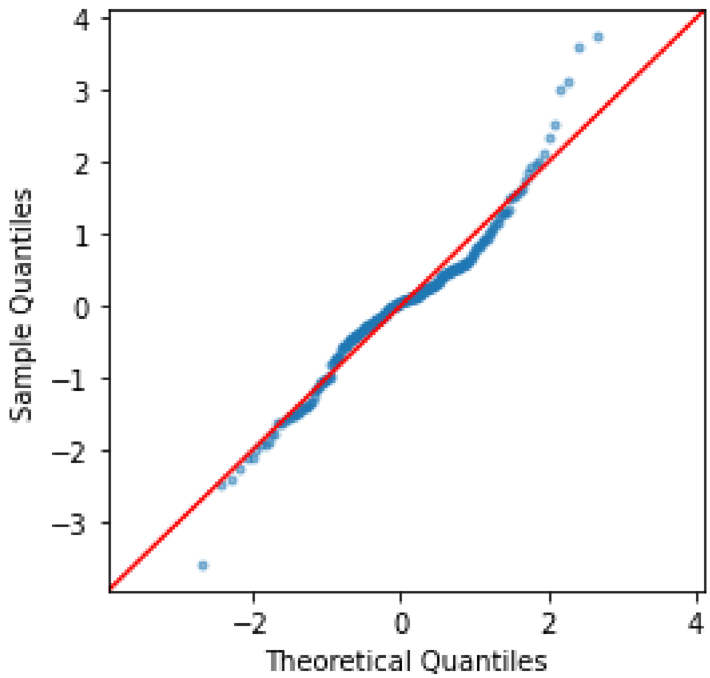
We proceed to inspect the residuals of the model. First we view the histogram of the residuals. It can be seen that it looks normal.

[84]:
```
plt.hist(residuals)
plt.ylabel('Frequency')
plt.xlabel('Residuals')
plt.savefig('./img/mdl_residuals.png')
plt.show()
```



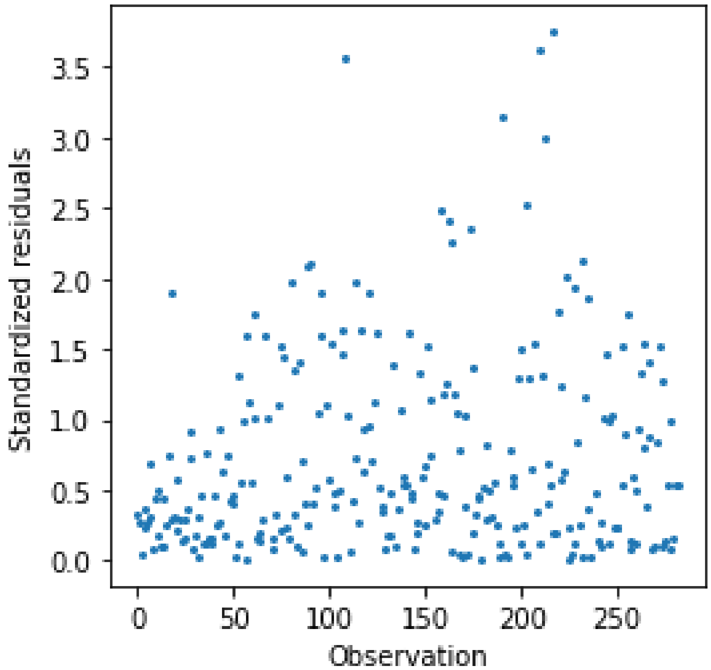
The next plot is a qqplot created to visually inspect the normality of the residuals. We see 3 nasty outliers in the top right corner.

[85]:
```
plt.figure()
ax = plt.gca()

qqplot(data=mdl.resid,
       ax=ax,
       color='#1f77b4',
       markersize=3,
       line='45',
       fit=True,
       alpha=1/2)

plt.savefig('./img/mdl_qq.png')
plt.show()
```



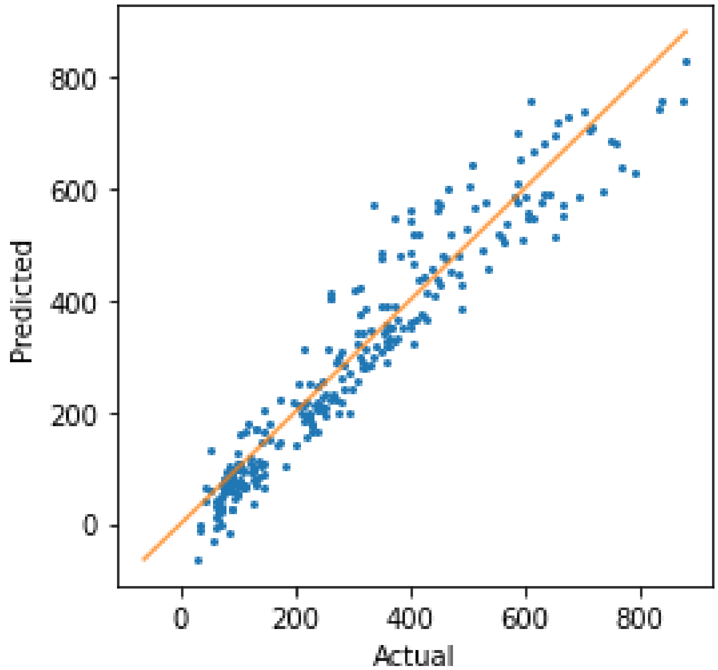
The third plot we make is a plot of the standardized residuals to check for homoskedasticity. Again we see the same outliers as on the plot above.

[86]:
```
residuals_std = np.abs((residuals - np.mean(residuals)) / np.std(residuals))
plt.plot(residuals_std, 'o', markersize=2)
plt.xlabel('Observation')
plt.ylabel('Standardized residuals')
plt.savefig('./img/mdl_residuals_std.png')
plt.show()
```



Finally we compare the predicted `kiloCalories` with the actual values.

[87]:
```
y_pred = mdl.predict(reg_df)
y_pred = y_pred.to_numpy().reshape(len(y_pred))

m = np.min(np.hstack([y_true, y_pred]))
M = np.max(np.hstack([y_true, y_pred]))

x = np.linspace(m, M, len(y_pred))
plt.plot(y_true, y_pred, 'o', markersize=2)
plt.plot(x,x, alpha=3/4)
plt.ylabel('Predicted')
plt.xlabel('Actual')
plt.savefig('./img/mdl_predicted_vs_actual.png')
plt.show()
```



The next step is to take a look at the data points with the biggest error. As can be seen the model has issues predicting strength training workouts.

[88]:
```
errors = reg_df.copy()
errors['kiloCaloriesPredicted'] = mdl.predict(reg_df)

errors['error'] = np.abs(errors['kiloCalories'] -␣
 ↪errors['kiloCaloriesPredicted'])

errors = errors.sort_values('error', ascending=False)
errors = errors.reset_index(drop=True)

order = ['kiloCaloriesPredicted',
         'kiloCalories',
         'error',
         'totalTime',
         'isStrength']

errors = errors[order]

errors = errors.head(5)

errors = errors.style.background_gradient(cmap='OrRd', subset='error')
errors = errors.set_precision(2)
```

```
errors
```

[88]: <pandas.io.formats.style.Styler at 0x7f1ce7d41a90>

9 Summary

[89]:
```
# Make table for README
# print(tabulate.tabulate(readme_df.values, readme_df.columns, tablefmt="pipe"))
```

- I downloaded data generated by my Polar watch that tracks `heart rate` and estimates burned `kilocalories` during workouts.
- The data came in the form of `.json` files which were read, transformed and cleaned with `pandas`.
- The clean dataset contains `283` workouts over a nearly one year period.
- After further transforming the data, I find that the `duration` of a workout and `kilocalories` burned have a `0.92` correlation.
- Several linear regressions were performed.
- `kilocalories ~ duration` on the entire dataset achieved `R^2 = 0.85` and `RMSE = 79`.
- Regressions were performed on subsets of the data, specifically by sport - the highest slope is 10.14 `kiloCalories` per minute.

Formula	Sport	Intercept	Slope	R squared
kiloCalories ~ totalTime	treadmill_running	-21.23	10.14	0.96
kiloCalories ~ totalTime	cycling	-9.73	7.44	0.98
kiloCalories ~ totalTime	walking	12.59	6.95	0.82
kiloCalories ~ totalTime	strength_training	-12.73	6.76	0.44

- A `linear mixed model with random effects` was created and validated. It achieved a `RMSE = 61`.
- The biggest errors made by the mixed model was on strength training data points.