Polar

October 03, 2023

1 Imports

[1]:
```python
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]:
```python
from IPython.display import display, HTML
```

2 Setup

[3]:
```python
# 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]:
```python
df = df.drop(['zones', 'samples', 'autoLaps',
              'laps', 'latitude', 'longitude',
              'ascent', 'descent'], axis=1)
```

[15]:
```python
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]:
```
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]:
```
def kcal_to_kg(x):
    return round(x / 7700, 2)
```

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

[38]: 11.61

7.4 Kilocalories burned by sport

[39]:
```
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]:

	Sport	Total kilocalories	Total kilograms
4	walking	33080	4.30
2	strength_training	31547	4.10

3	treadmill_running	19825	2.57
0	cycling	4029	0.52
1	running	940	0.12

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.

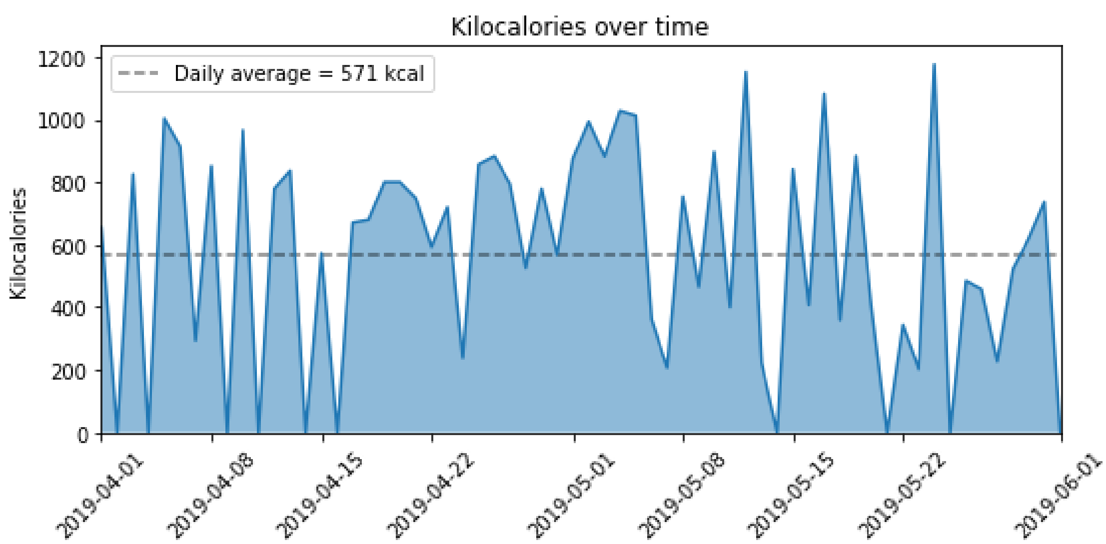
[41]:
```
dates = pd.date_range(start, stop)
dates = dates.to_frame()
dates = dates.reset_index(drop=True)
dates.columns = ['startTime']
```

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

Finally we produce the figure:

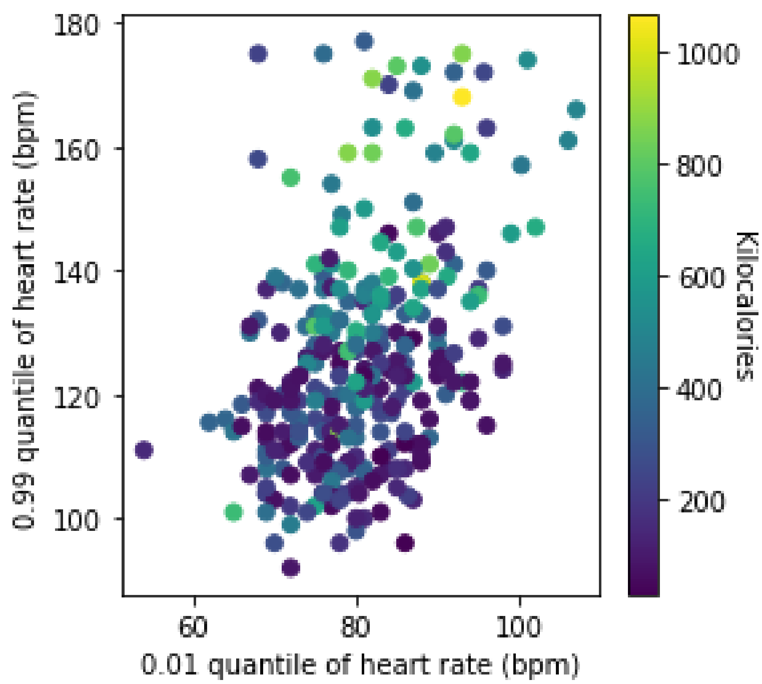
[43]:
```
width = 800
height = 400
dpi = 100

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]:
```
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]:

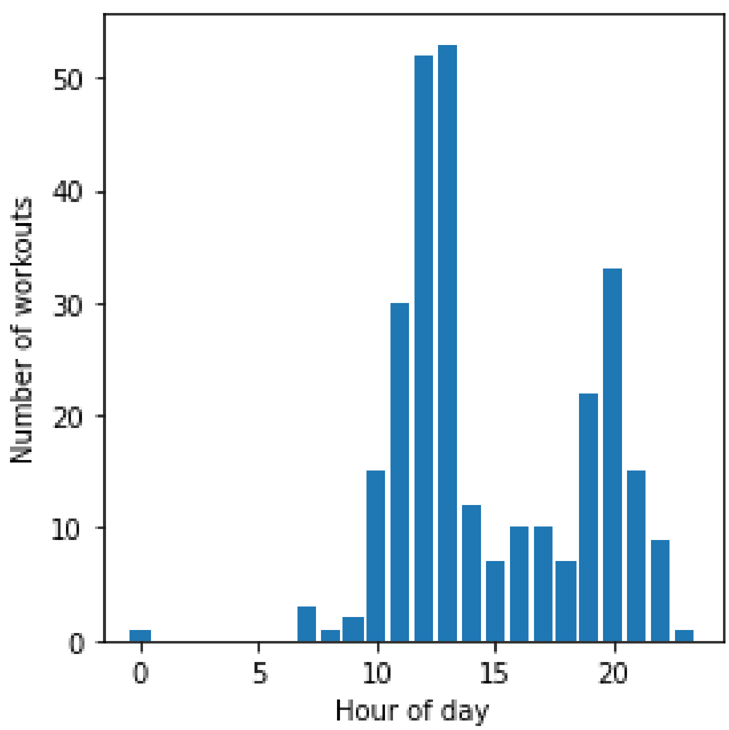
	Sport	Count
4	walking	105
3	treadmill_running	90
2	strength_training	62
0	cycling	24
1	running	2

7.8 By hour of day

We count workouts by hour of day.

[46]:
```
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.tight_layout()
plt.savefig('./img/workouts_by_hour_of_day.png')
plt.show()
```

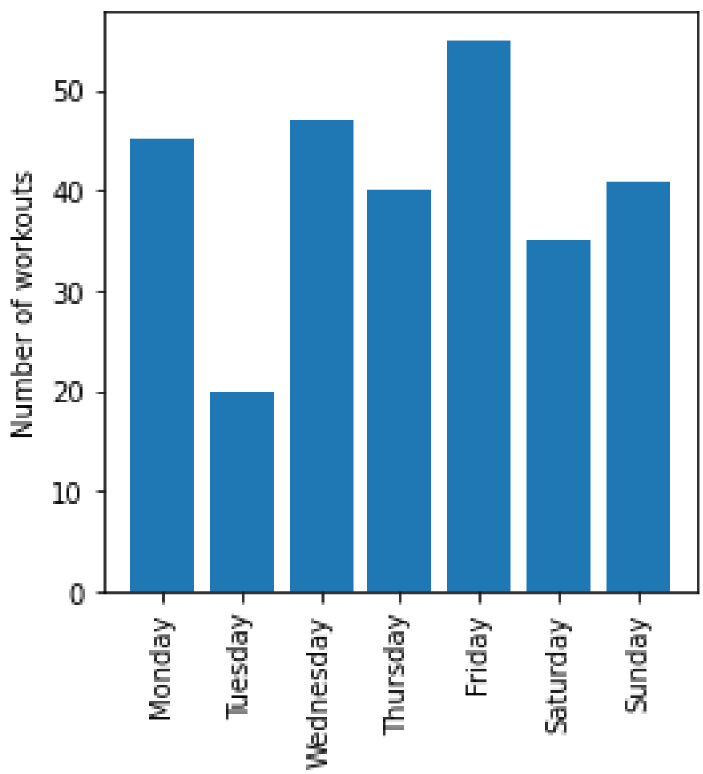


7.9 By day of week

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"})
```

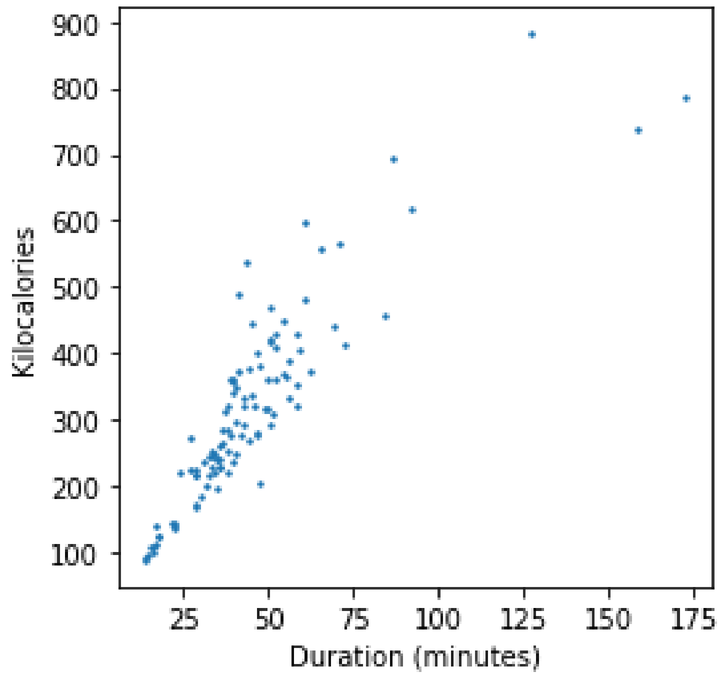
[49]:
```
plt.bar(by_day["Day of week"], by_day["Total Workouts"])
plt.xticks(rotation=90)
plt.ylabel("Number of workouts")
plt.savefig("./img/workouts_by_day_of_week.png")
plt.show()
```



7.10 Scatter plot of walks data

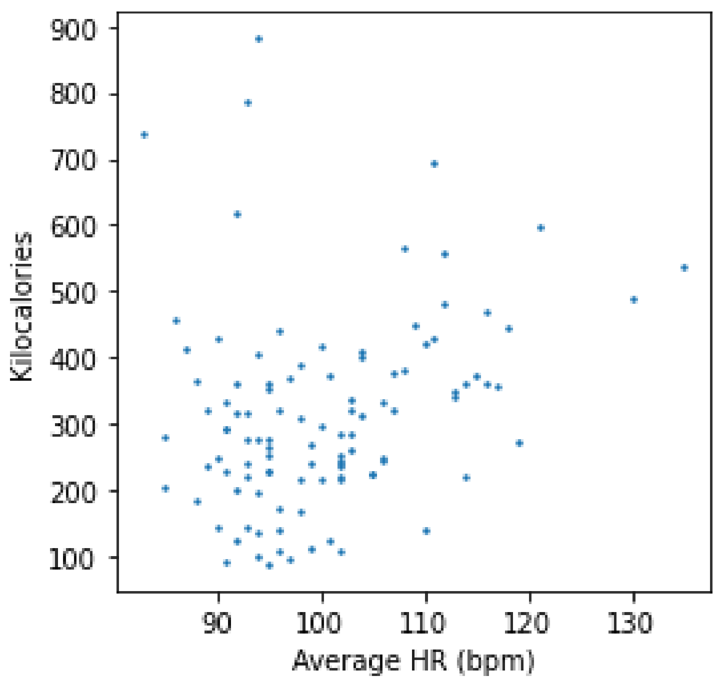
We plot totalTime versus kiloCalories. As can be seen their seems to exist a linear relationship between the two.

[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
```

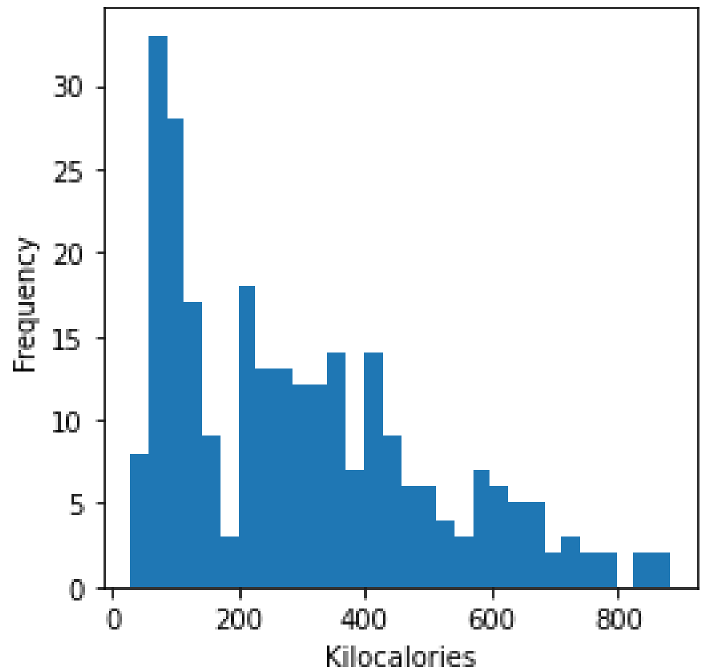
[56]:
```python
time_mask = is_outlier_iqr(series=reg_df['totalTime'])
kcal_mask = is_outlier_iqr(series=reg_df['kiloCalories'])
hr_mask = is_outlier_iqr(series=reg_df['heartRateQ99'])
```

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

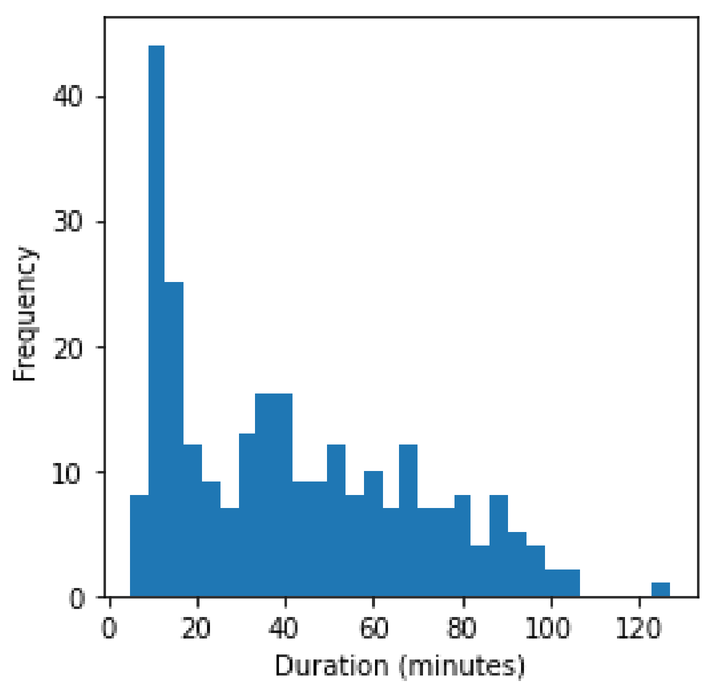
8.2 Histograms

We proceed to visualize histograms of each of the variables.

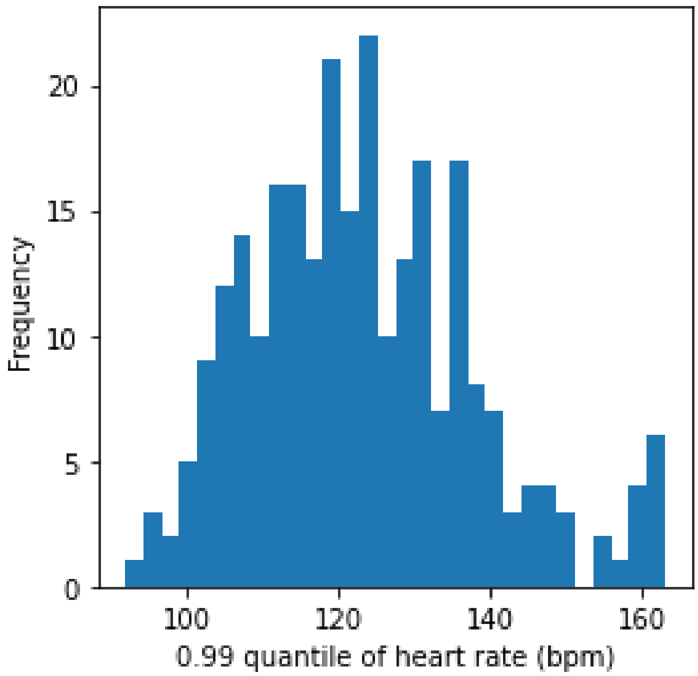
[58]:
```python
plt.hist(reg_df['kiloCalories'], bins=30)
plt.xlabel('Kilocalories')
plt.ylabel('Frequency')
plt.savefig('./img/kilocalories_histogram.png')
plt.show()
```



[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()
```

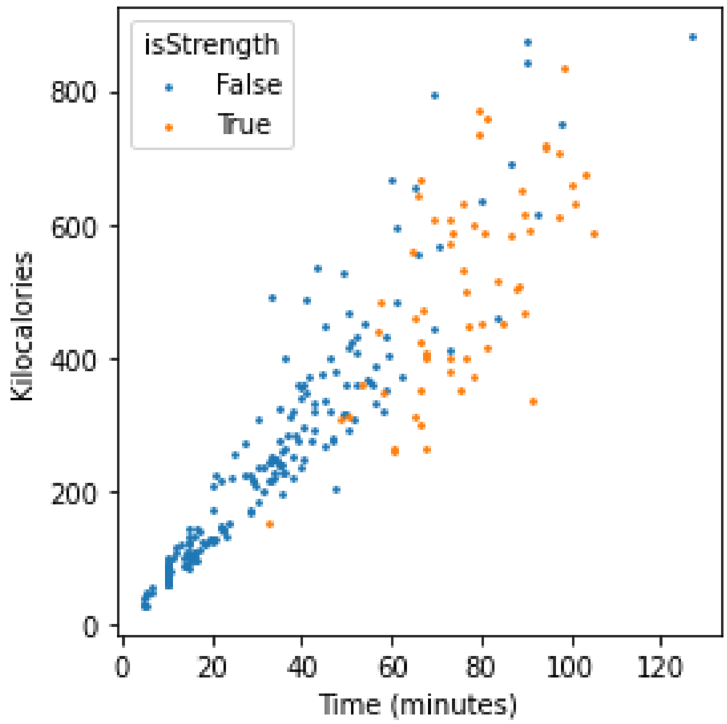


8.3 Scatter plots

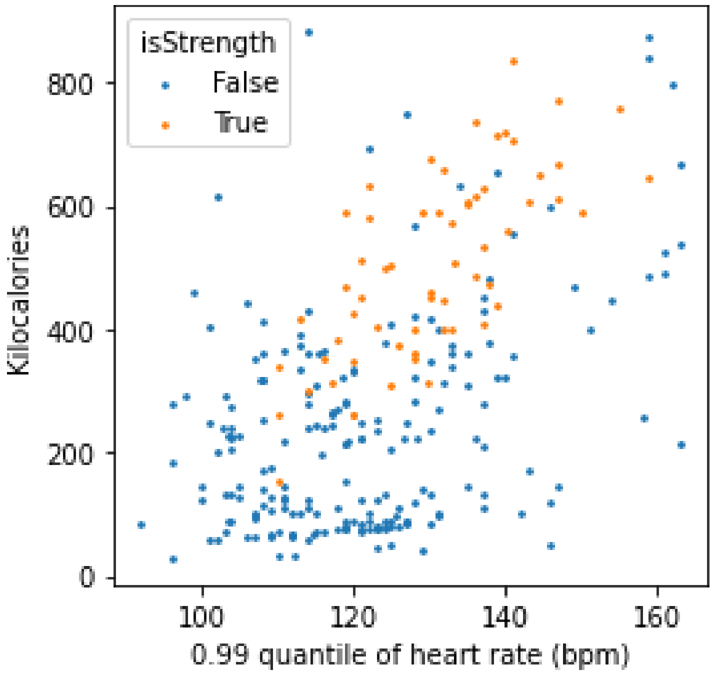
The plot below gives reason to suspect a linear relationship between kiloCalories and totalTime.

[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.tight_layout()
plt.savefig("./img/time_vs_kilocalories_scatter_by_strength.png")
```

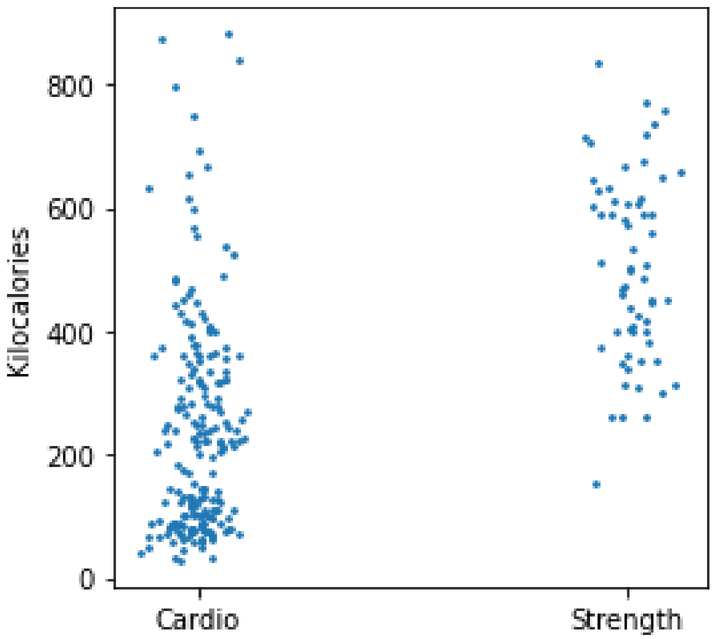
```
plt.show()
```



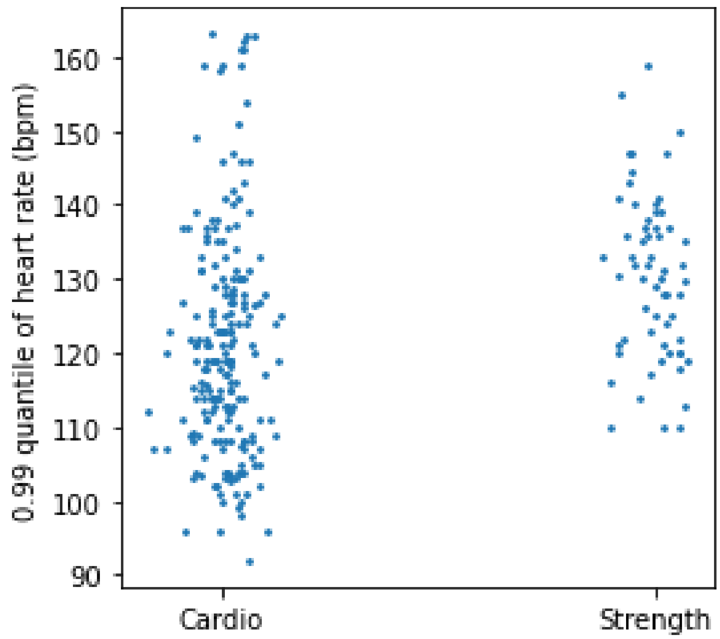
[62]:
```
for val in [False, True]:
    tmp = reg_df[reg_df['isStrength'] == val]
    plt.scatter(tmp['heartRateQ99'],
                tmp['kiloCalories'],
                s=3,
                label=val)

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()
```



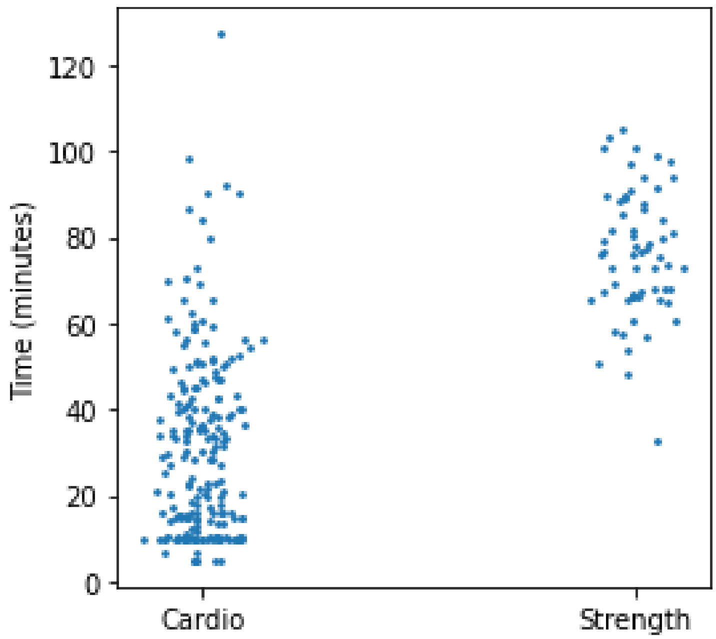
[63]:
```
plt.scatter(reg_df['isStrength'] + np.random.normal(scale=1/20,␣
↪size=len(reg_df)),
            reg_df['kiloCalories'], s=3)

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] :

	kiloCalories	totalTime	heartRateQ99	isStrength
kiloCalories	1.00	0.92	0.51	0.55
totalTime	0.92	1.00	0.28	0.69
heartRateQ99	0.51	0.28	1.00	0.26
isStrength	0.55	0.69	0.26	1.00

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))

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] :

	Variable	VIF
0	totalTime	6.30
1	heartRateQ99	3.90
2	isStrength	2.41

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

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

[71]:
```
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]:
```
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:                 2020-10-06 10:25 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]:

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

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:               2020-10-06 10:25 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]:

	RMSE	Formula	Random effects	Groups
1	58.03	kiloCalories ~ totalTime + heartRateQ99	None	None
2	60.92	kiloCalories ~ totalTime + heartRateQ99	~ totalTime	isStrength
0	78.78	kiloCalories ~ totalTime	None	None

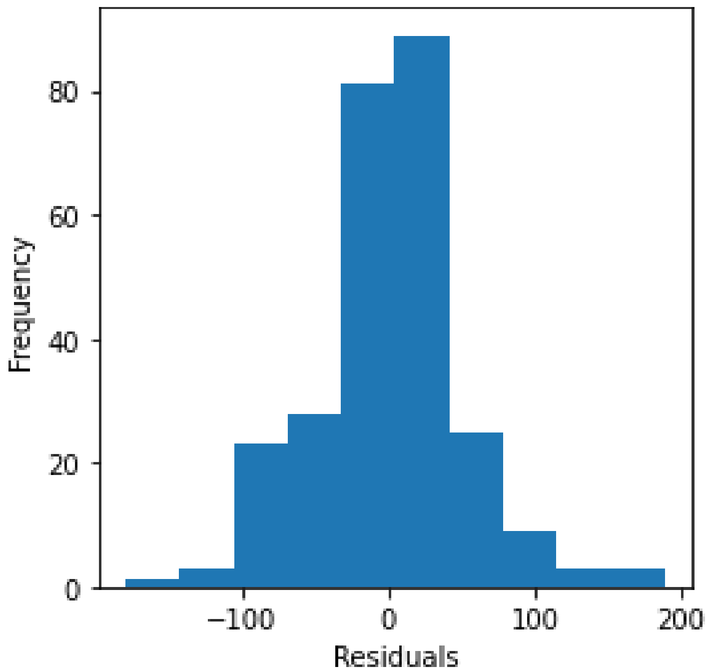
For further evaluation we choose the random effects model.

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

8.9.1 Visual inspection

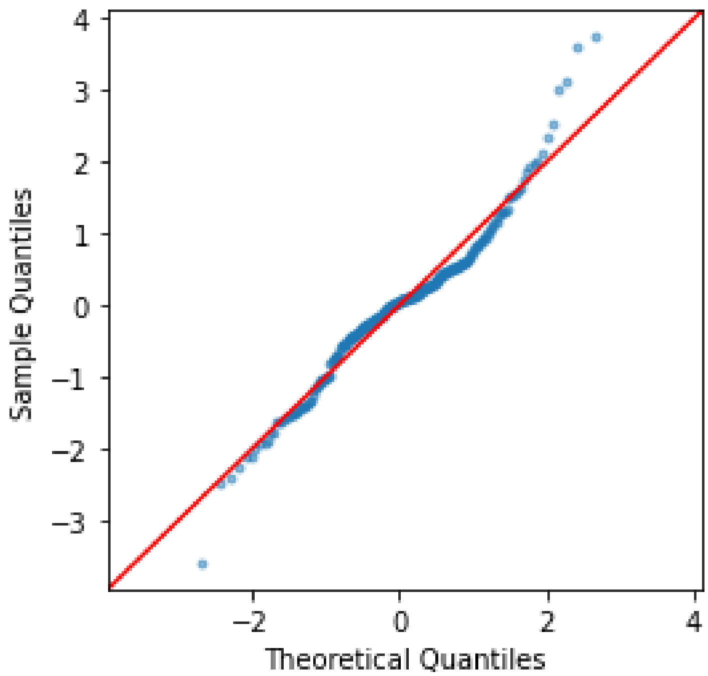
We proceed to inspect the residuals of the model. First we view the histogram of the residuals. It can be seen that it looks normal.

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



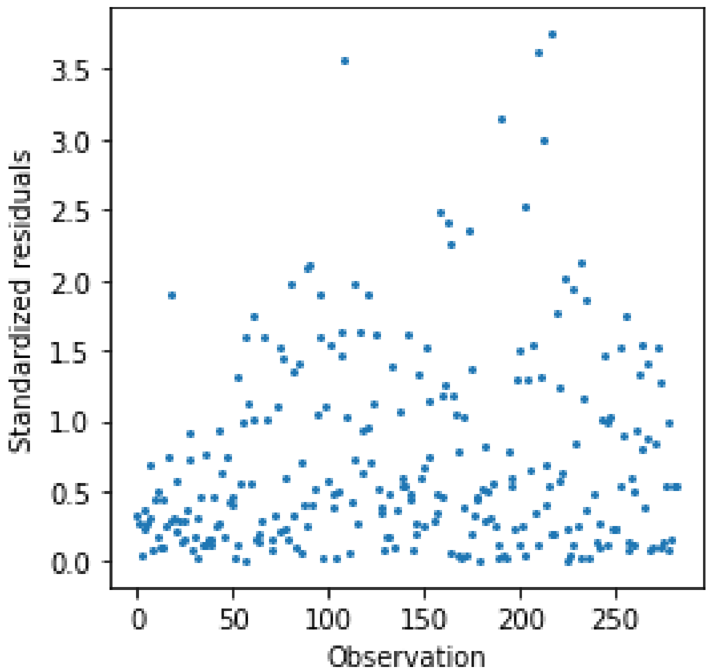
The next plot is a qqplot created to visually inspect the normality of the residuals. We see 3 nasty outliers in the top right corner.

[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()
```



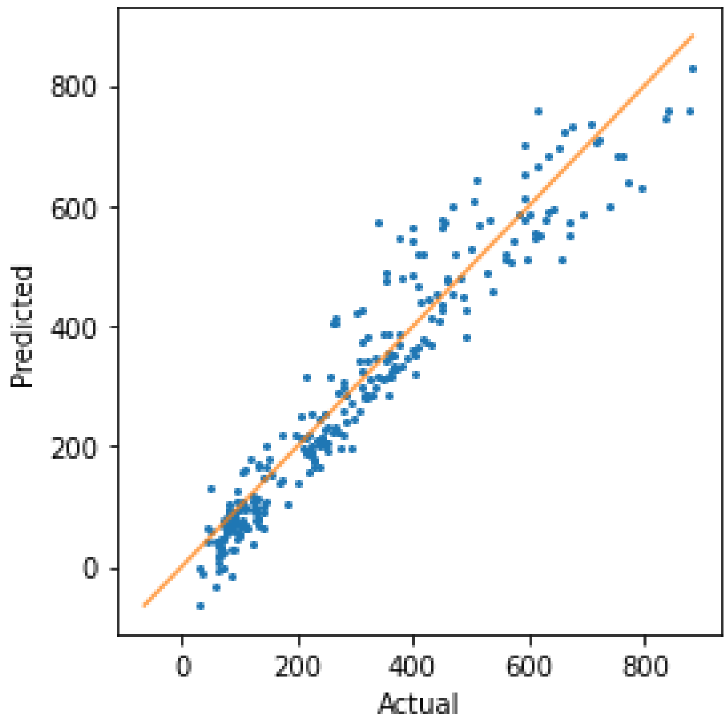
The third plot we make is a plot of the standardized residuals to check for homoskedasticity. Again we see the same outliers as on the plot above.

[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.tight_layout()
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]:
```python
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 0x7f8538793640>

9 Summary

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

[90]:
```
# Make table for README
# print(tabulate.tabulate(readme_df.values, readme_df.columns, tablefmt="pipe"))
```

- In this project I define a `workout` as each instance in time when my watch was recording me.
- 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 during which I burned roughly `12kg` of body fat.

Sport	Total kilocalories	Total kilograms
walking	33080	4.3
strength_training	31547	4.1
treadmill_running	19825	2.57
cycling	4029	0.52
running	940	0.12

- The timing of my workouts appears to follow a `bimodal distribution` with peaks at `12:00` and `20:00`.
- After further transforming the data, I find that the `duration` of a workout and `kilocalorie`'s 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
kilo_calories ~ total_time	treadmill_running	-21.23	10.14	0.96
kilo_calories ~ total_time	cycling	-9.73	7.44	0.98
kilo_calories ~ total_time	walking	12.59	6.95	0.82

Formula	Sport	Intercept	Slope	R squared
kilo_calories ~ total_time	strength_training	-12.73	6.76	0.44

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